

A topographic map of the Colorado River Basin, showing the intricate network of the river and its tributaries. The terrain is depicted in shades of brown and tan, with a prominent snow-capped mountain peak in the lower right quadrant. The river's path is highlighted in a dark, winding line across the landscape.

Colorado River Basin Climate and Hydrology State of the Science

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Colorado River Basin Climate and Hydrology

State of the Science

April 2020

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Colorado River Basin Climate and Hydrology

State of the Science

Executive Summary

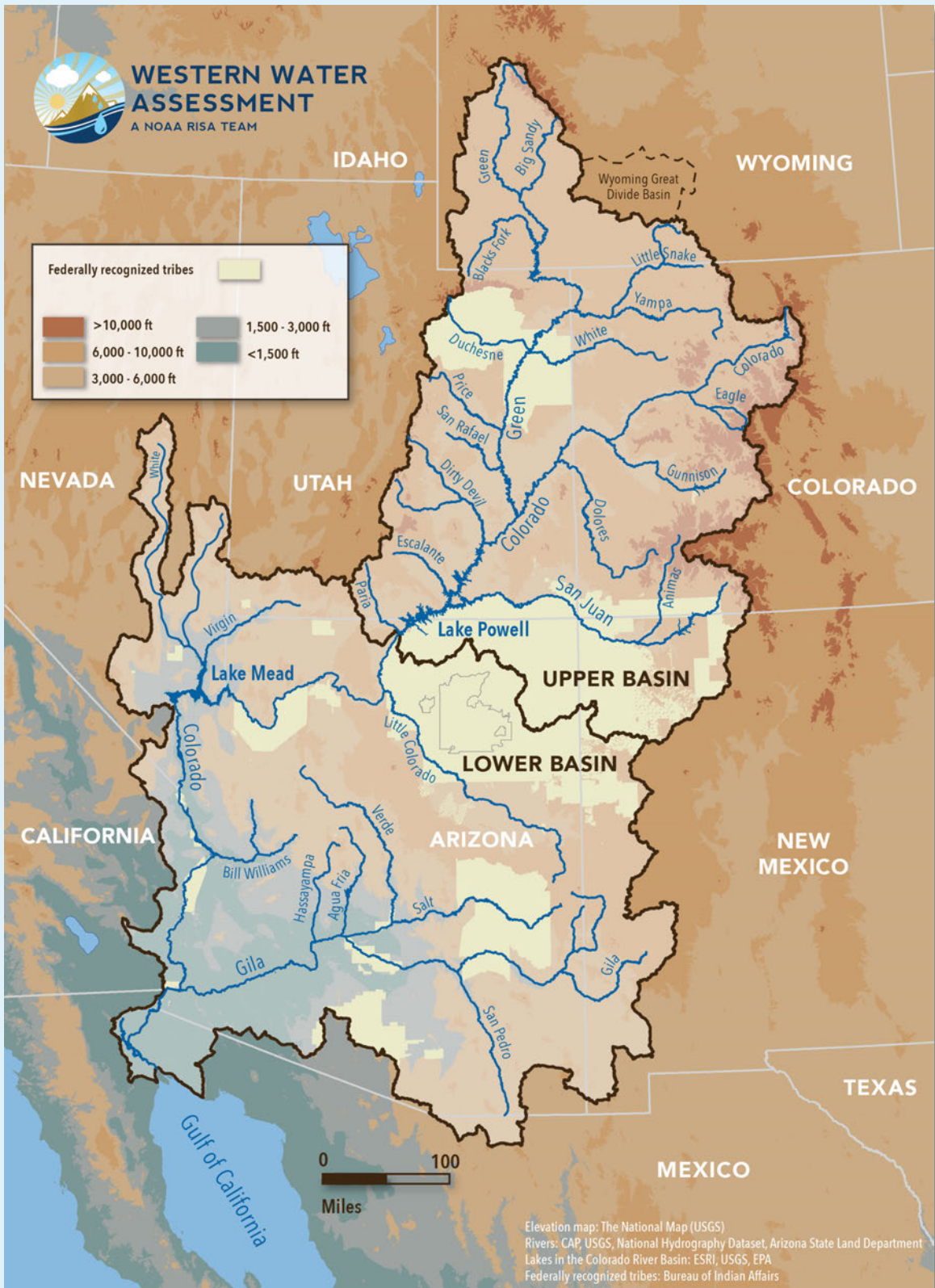
The Colorado River Basin currently faces unprecedented stresses. Persistent dry conditions since 2000, along with the increasing recognition that warming temperatures are impacting the hydrology of the basin, have led to great concerns about the long-term reliability of basin water supplies. With ever-higher stakes for water resource planning and decision making, an even greater emphasis is placed on the tools that support those activities, notably Reclamation's operations and planning models and similar models used at other agencies. The usefulness of these system models depends on many types of datasets and forecasts that serve as inputs to them, as well as the research and scientific understanding underpinning this complex chain of data and models. The development and refinement of the different links of the chain necessarily involves researchers, forecasters, and water managers.

New research efforts have advanced our understanding of the hydroclimate of the basin and how key hydroclimate processes, variability, and changes can be captured in data and models. This rapid expansion of the scientific knowledge base, and the increasing complexity of the data and models used to operationalize that knowledge, parallel the growing uncertainties about the future climate and hydrology. Accordingly, basin stakeholders have recognized the importance of reassessing the scientific and technical basis for management and planning.

By synthesizing the state of the science in the Colorado River Basin regarding climate and hydrology, this report seeks to establish a broadly shared understanding that can guide the strategic integration of new research into practice. The ultimate goal of that integration, and therefore of this report, is to facilitate more accurate short- and mid-term forecasts, and more meaningful long-term projections, of basin hydroclimate and system conditions.

Past scientific advances have led to improvements in the various links in the chain of data and models, and to more accurate and actionable information for decision making. The ongoing efforts documented in the report strongly suggest that this progress will continue. At the longer time scales, however, research reveals and affirms large uncertainties that are difficult to reduce given both natural variability and the imperfections in our understanding, observations, and models, and our inability to fully test our predictions.

Each chapter of the report focuses on one major link in the chain of data and models, covering a broad array of activities to better observe, model, forecast, and understand the climate and hydrology of the basin. Key points from each chapter are presented below, as well as a summary of the challenges identified in each chapter and the opportunities to address those challenges. Readers are encouraged to explore the full report for the context supporting these key points and challenges and opportunities.



The Colorado River Basin

Chapter 2. Current Understanding of the Colorado River Basin Climate and Hydrology

Key points

- On average, about 170 million acre-feet (maf) of precipitation falls over the Colorado River Basin annually, but only about 10% (17 maf) becomes natural streamflow available for use.
- The Upper Basin contributes the vast majority, about 92%, of the total basin natural streamflow as measured at Imperial Dam.
- Elevation dramatically shapes the amount of precipitation and its relative contribution to runoff, so that 85% of annual runoff comes from the 15% of the basin's area that is located in the mountain headwaters.
- The position and activity of the mid-latitude storm track from October through May is the critical climatic driver of annual precipitation in the basin's headwaters.
- Snowmelt is the primary source of annual runoff from those mountain headwaters, as reflected in the prominent late-spring peak in the annual hydrograph.
- Year-to-year variability in runoff is high and is mainly driven by variability in precipitation; decadal and multi-decadal variability in precipitation and in runoff is also present but no consistent cycles have been identified.
- The predictability that does exist at shorter time scales (up to 1 year) comes mainly from the El Niño-Southern Oscillation (ENSO); the ENSO signal is generally weak in the Upper Basin but stronger in the Lower Basin.
- Predictability at decadal and longer time scales using longer-lived climate phenomena (e.g., Atlantic Multidecadal Oscillation, Pacific Decadal Oscillation, etc.) has proven elusive.
- The period since 2000 has been unusually drought-prone, but even more severe and sustained droughts occurred before 1900.
- There has been a substantial warming trend over the past 40 years; the period since 2000 has been about 2°F warmer than the 20th-century average, and likely warmer than at any time in the past 2000 years.
- Decreases in spring snowpack and shifts to earlier runoff timing in many parts of the Upper Basin, as well as decreases in annual Colorado River flows at Lees Ferry, Arizona, have occurred in recent decades. These changes in hydrology can be linked, at least in part, to the warming trend.



Challenges and opportunities

Challenges

- There is still considerable uncertainty in the quantification of the relative roles of temperature, precipitation, antecedent soil moisture, dust-on-snow, and vegetation change in recent and ongoing variability and change in Upper Basin snowpack and streamflow.
- These factors have substantial spatial variability, but most studies have conducted analyses and presented findings only at the Upper Basin-wide scale (e.g., at Lees Ferry).

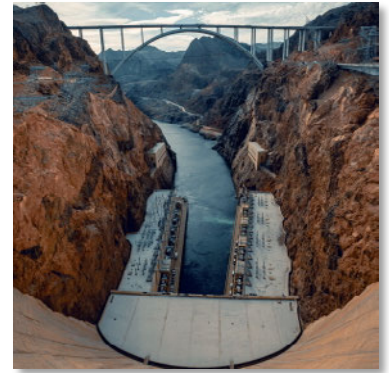
Opportunities

- Conduct analyses of Upper Basin hydrologic change that are spatially disaggregated at least to the eight major sub-basins (Upper Green, Yampa-White, etc.), or focus only on the most productive headwaters areas, or both.
- Pursue the various pathways to improve hydrologic modeling presented in Chapter 6.
- Conduct intercomparisons of hydrologic models and statistical methods for assessing the factors behind hydrologic changes.

Chapter 3. Primary Planning Tools

Key points

- Three monthly Reclamation models, developed in RiverWare™, support planning at three time scales: 1) 24-Month Study (24MS) for short-term planning (up to 24 months), 2) Mid-Term Probabilistic Operations Model (MTOM) for mid-term planning (up to 60 months), and the Colorado River Simulation System (CRSS) for long-term planning (multiple decades).
- The models use rules to incorporate operational policies set forth in Records of Decisions and other operational agreements, and some long-term studies also explore potential alternative policies.
- Hydrologic inputs to the short-term and mid-term models are either flows forecast by the NOAA Colorado Basin River Forecast Center (CBRFC) or statistical averages of observed flows.
- Hydrologic inputs to the long-term model may be based on historical hydrology, paleohydrology, climate change-informed hydrology, or hybrids.
- Measured Upper Basin water demands for the short-term and mid-term models are accounted for in the CBRFC's forecast; Lower Basin water demands are provided by Lower Basin water users and Mexico. Both Upper and Lower Basin demands for the long-term model are based on projections supplied by water users.
- Uncertainties, errors, and limitations arise from input data sources, assumptions about the future, and necessary simplifications of a complex water supply system.



Challenges and opportunities

Challenge

Each Reclamation model (24MS, MTOM and CRSS) has different ways that uncertainty can be better quantified and either addressed or incorporated. In particular, each model uses a more simplistic method for projecting future inflows in the Lower Basin than in the Upper Basin (5-year averages for 24MS and MTOM rather than a forecast, and gaged flow in CRSS rather than natural flow). In the Upper Basin, demand projections may differ from actual water use trends and the representation of complex operating policies via rules deployed at the monthly time step may further contribute to this deviation. Finally, more in-depth analyses are needed to verify how well modeled operational policies reflect actual operations.

Opportunities

- Complete the Forecast and Reservoir Operation Modeling Uncertainty Scoping (FROMUS) report and update its findings as models are refined.
- Work with the CBRFC to develop unregulated flow forecasts for the Lower Basin.
- Continue to work toward commitments outlined in the Colorado River Basin Study regarding the development of natural flows in the Lower Basin.
- Work with Upper Basin states, water users, and tribes to refine long-term demand projections.
- Complete hindcasting studies that can help identify how simplifications in Reclamation’s models contribute to projection error.

Challenge

The coarse spatial resolution in CRSS has implications for studying demands and tributary flows. In the Upper Basin, water demands are represented in highly aggregated nodes and do not reflect water right priorities, which limits the ability to accurately model shortages to specific users under different scenarios. On the Lower Basin tributaries, because gaged flow is used rather than natural flow, demands are not explicitly modeled. CRSS uses a monthly time step that limits the ability to analyze the impacts to certain resources, in particular, ecological resources. Additionally, the exclusion of smaller tributaries limits the analyses that can be performed with CRSS.

Opportunities

- Review the configuration, number of nodes, and rules in the Upper Basin to explore implementing an allocation system that captures the distribution of water supply by water rights priority.
- The quality, coverage, and resolution of data that is used to naturalize inflows has improved and might support model disaggregation in both time and space.
- Explore iterative sub-basin implementations that are solved at shorter time scales or finer resolutions and that may be aggregated and fed into existing nodes in CRSS.

Challenge

Reclamation models are complex and the projections they generate are the product of combinations of many data sources and assumptions. It is critical that stakeholders and the public understand the uncertainty and how this uncertainty affects projections of risk in order to ensure the appropriate use of the results for decision making. Reclamation continues

to work toward improving such communication but there is room for improvement. Additionally, the models are not comprehensively documented, despite their critical importance in Colorado River Basin management and planning.

Opportunities

- Continue to improve and refine communication of model assumptions and uncertainty on Reclamation’s modeling website and in widely distributed modeling results (e.g., the 24MS reports).
- Develop comprehensive, technical overviews of each of the models to share how each model is configured, how the rules are implemented, and how the inputs are derived.

Chapter 4. Observations—Weather and Climate

Key points

- Weather and climate data are collected and interpolated for specific reasons, so not all data and datasets are suitable for all uses. Users should be cautious about “off-label” use of climate data and should thoroughly investigate the suitability of data before it is applied outside of its planned uses.
- Users of weather and climate datasets should be aware that the data reflect average or summary conditions over their spatial and temporal resolution and should not expect a gridded product to accurately reflect conditions at any particular point on the landscape at any given point in time. This is particularly true for high-relief landscapes like the Colorado River Basin.
- Most of the existing high-resolution gridded datasets share some base information or use similar processing, or both, so they are not strictly independent.
- There is not now, and likely never will be, perfect weather and climate data. Producers of climate information need to communicate, and users should be cognizant of, the strengths and weaknesses of the data they choose and how climate data choices influence their conclusions.
- In the Colorado River Basin, the highest elevations have the lowest weather station densities and likely the least precise and accurate weather information. This is especially problematic for water resource questions, because such a large fraction of the runoff is generated at high elevations.



Challenges and opportunities

Challenge

While commonly used gridded climate datasets show very similar variability and trends in precipitation and temperature for the basin, disagreements between the datasets are larger for the sparsely instrumented high-elevation areas in the Upper Basin—the areas that generate the vast majority of the basin’s runoff.

Opportunities

- Use other types of measurements, such as streamflow and radar, to constrain the gridded estimates of temperature and precipitation, and add novel observation techniques (e.g., Airborne Snow Observatory) to bolster ongoing observations.

- Use numerical weather prediction models for spatiotemporal interpolation and validation of observation-based products.

Challenge

It is increasingly understood that the gridded climate datasets have inherent uncertainties and differ from each other, but how those uncertainties and differences manifest in the outputs of typical hydroclimate modeling and analysis tasks needs to be better explored and communicated to users.

Opportunities

- Conduct formal intercomparisons between gridded datasets in the context of specific applications and outputs (e.g., Alder and Hostetler 2019 on the use of different gridded climate datasets for statistical downscaling of GCM data).
- Application projects can consider including a testing phase in which multiple gridded datasets are tested on a limited portion of the project's domain or analyses.
- Both researchers and users can acknowledge that all data are imperfect, and move away from trying to identify a single “best” product toward greater consideration of the data characteristics that are, and are not, important for their questions and analyses.

Chapter 5. Observations—Hydrology

Key points

- Robust real-time observations and long-term records of snowpack, streamflow, soil moisture, and other hydrologic variables are key inputs to basin streamflow forecasting and system modeling.
- Point measurements of these variables are not dense enough to fully represent spatial variability across the basin, and not necessarily sited to optimally inform streamflow forecasts.
- For snowpack observations, the in situ SNOTEL network has limitations but remains essential to monitoring and skillful streamflow forecasting.
- Spatially distributed snowpack data from models and remote sensing are increasingly used to augment SNOTEL data, though most of these sources depend on SNOTEL data for calibration.
- Accurate and useful streamflow inputs depend on both the robustness of the gage network and the procedures used to adjust and naturalize gaged streamflows to account for human activity.
- Flow naturalization methods try to estimate what the streamflow at a gage would have been, or will be, without the impacts of upstream human activity; naturalization methods vary from agency to agency, depending on the time scale and application.
- Evaporation and evapotranspiration estimates are central to flow naturalization, thus as more types of observations become available, models used to calculate these variables are being refined in both physical process modeling and input data used.
- In situ measurements of soil moisture and evaporation-related variables are especially sparse, and spatially distributed data from models and remote sensing have a larger role to play in condition monitoring and streamflow forecasting.
- Realizing the full value of spatially distributed hydrologic data will ultimately require streamflow-forecasting and system-modeling frameworks that are explicitly designed to use those data as inputs.



Challenges and opportunities

Challenges: Snow

- Inadequate characterization of the snowpack is still a major source of error in streamflow forecasts, especially in years with anomalous patterns of snow distribution in space and time—a phenomenon which appears to be more frequent in a changing climate

- The in situ (point) snow course and SNOTEL network was designed for the statistical streamflow forecasting paradigm, which is no longer used by CBRFC.
- Many new spatially distributed SWE products are now available, but there have been few rigorous evaluations of these datasets, in part because it is difficult to validate spatial products with point measurements.
- The SNOTEL network will remain essential to any conceivable future snow monitoring system in the basin, especially with additional sensor capacity at SNOTEL sites, but the network has been inadequately supported in recent years by USDA.

Opportunities

- Building on recent smaller scale pilot efforts to conduct larger scale, systematic intercomparisons of SWE datasets and products for the basin, including SNOTEL, ASO, and SNODAS and other spatially distributed modeled products.
- Based on the results of such intercomparisons, pursuing “hybrid” approaches where multiple methods and datasets are combined in a way to best exploit their relative advantages.
- Continuing and stepping up the modernization and expansion of the SNOTEL network, with more and better sensors, more imagery, and better data communication—all of which would necessitate more resources for NRCS to support the network.

Challenges: Streamflow

- Streamflow observations that could contribute to more accurate naturalization calculations are not available at many key sites, especially diversion and return flow locations.
- Naturalizing the gage record requires adjustments that come with potential errors and uncertainties, many of which are impossible to address or resolve because of the dearth of early-period data and documentation.
- Fully characterizing the natural hydrology of the basin is problematic with the exclusion of the Gila River from consideration.
- A number of research activities use Reclamation’s natural flow record for baseline or reference purposes. For example, synthetic streamflow generation relies on the natural flow record for parameter estimation or for nonparametric sampling, tree-ring reconstructions of paleostreamflows are calibrated against the natural flows at Lees Ferry, and hydrologic simulations from the Variable Infiltration Capacity

model that are used to project future streamflows were bias-corrected based on the natural flows at Lees Ferry and other gaging stations.

Opportunities

- Regarding gaging, the biggest gains in information going forward would be achieved by expanding the streamflow monitoring network to fill gaps in coverage. This includes gages at diversion sites and in locations to measure return flows or verify return flow and gain/loss calculations.
- Increasing the spatial resolution of Reclamation's models might be a useful avenue to pursue in order to simulate and analyze impacts from climate change on sub-basin hydrology.
- Major modifications to the natural flow record, to improve consumptive use estimates for example, have implications for both the calibrations and other applications listed above, and for the record extension back to 1906 because the extended records were based on statistical analyses of the natural flow record that was in place at the time of extension. As more recent natural flow data becomes available, there is an opportunity to revisit the characterizations, calibrations, bias-corrections, and record extension that were based on earlier versions of the natural flow record.

Challenges: Soil moisture and evaporation

- Compared with snowpack (which is variable over space and time), soil moisture is poorly monitored and understood, with frequent discrepancies between in situ measurements and modeled estimates.
- Real-time soil moisture data is collected from at least 6 different in situ networks, with differing observing protocols (depth, etc.).
- Reservoir evaporation estimates as used in basin system modeling have been based on decades-old data that does not reflect current climate conditions.
- Estimates of evapotranspiration and crop water use have been constrained by physically incomplete methods and input data that are not spatially representative.

Opportunities

- Support and expand ongoing efforts to comprehensively collate in situ soil moisture measurements and merge these observations with spatially distributed modeled estimates (e.g., National Soil Moisture Network).
- New satellite sensors and products (e.g., SMAP) that provide spatially comprehensive and consistent soil moisture estimates can likewise be compared and blended with other types of soil moisture data.

- When applicable, conduct testing of new soil moisture products to determine if they add value to the CBRFC forecast process.
- Ongoing efforts will provide updated reservoir evaporation estimates for Lakes Mead and Powell; those efforts could be expanded to other large reservoirs in the basin.
- Expand the in situ monitoring of evaporation/ET/PET with enhanced weather stations that capture all four variables needed for fully physical estimates (e.g. the Penman-Monteith method), and new flux towers needed for the Eddy Covariance method.
- Better in situ data will also help in calibrating/validating remote sensing-based spatial estimates of ET and crop water use; use of these spatial estimates in the basin has been increasing, though it has been limited by user confidence in the data.

Chapter 6. Hydrologic Models

Key points

- With a range of hydrologic models readily available, it is important for prospective applications of models to articulate the objectives of the modeling as well as the requirements that the model must satisfy.
- A single model is likely designed for a specific application or context and may not be optimal for a wider range of uses.
- In the Colorado River Basin, the NWS models (streamflow forecasting) and the VIC model (sensitivity studies; climate change projection) have been the most-consulted hydrologic models for those respective applications. Each has varying capabilities and limitations.
- Increasing model complexity does not guarantee improved model performance. Complexity should be increased subject to the consideration of process needs, data sufficiency, computational feasibility, and ultimately the model's demonstrated performance.
- For some applications, such as streamflow forecasting at a river location, simpler models may continue to offer valuable and even superior performance for years to come.
- For other applications, such as understanding hydrologic sensitivity to climate change or hydrologic response to watershed changes, more complex process-oriented models are usually more appropriate.
- Calibration (parameter estimation) is almost always needed to achieve high-quality simulations in all hydrologic models, and it is easier to implement in simpler models than in computationally intensive complex models.



Challenges and opportunities

Challenge

The conceptual modeling approach used in operational forecasting is not well-suited to take full advantage of advances in process understanding and modeling. The process-complexity of the models used for short-range to seasonal forecasting could be increased, albeit in a careful manner. This must be done within a strategy that acknowledges and provides for commensurate changes in operational workflows, including the development of data assimilation approaches.

Opportunity

- Implement a testbed framework for operational modeling that can incrementally advance and benchmark modeling improvements for

different objectives, evaluating and justifying increases in complexity based on model performance.

Challenge

Distributed regional parameter estimation remains a vexing scientific challenge, and there is a critical need for accessible, efficient model calibration approaches to avoid the use of semi-calibrated land surface models in water supply applications (e.g., climate-change impact assessment). Without this capability, no model will perform well, and watershed-tuned conceptual models will be hard to outperform.

Opportunity

- Multiscale Parameter Regionalization (MPR) offers promise but will require more development to leverage both the strengths of the attribute-based parameter development and the greater optimization potential in individual basins. Improved understanding of parameter sensitivities in models such as VIC, multi-objective calibration (considering more variables than just streamflow), and broader use of geophysical attributes, may offer near-term paths for improvement.

Challenge

The widespread use of VIC and similar land surface models for climate change impact studies may have inadvertently limited the exploration and quantification of projected hydrologic changes. There is a need to identify processes that are not represented in models such as VIC and that lead to hydrologic impacts that affect stakeholders (such as dust-on-snow), and to require that models used in climate-change impact studies a) include parameterizations to represent those processes, and b) demonstrate that their process performance is realistic.

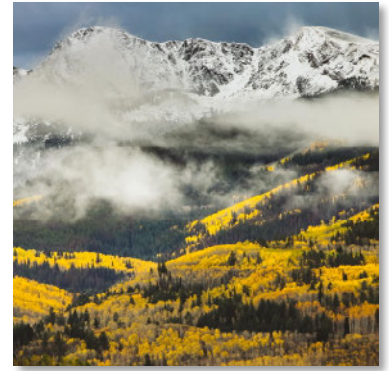
Opportunity

- New models and modeling frameworks such as SUMMA, Noah-MP, WRF-Hydro, and CTSM may offer a more flexible foundation for enhancing model process complexity in appropriate, and carefully benchmarked ways. Process parameterizations in individual models may be leveraged to expand the range of options in flexible model frameworks. This activity will ideally be deliberate, pursuing targeted model improvements and motivated by stakeholder needs assessments, rather than top-down or wholesale adoption of an alternate off-the-shelf model.

Chapter 7. Weather and Climate Forecasting

Key points

- Uncertainty about upcoming weather and climate conditions translates into a major source of uncertainty in seasonal streamflow forecasts.
- Weather forecasts out to 10 days have relatively high skill and are progressively improving; they are incorporated into the CBRFC's operational streamflow forecasts.
- Sub-seasonal (2 weeks to 12 weeks) and seasonal (3 months to 1 year+) climate forecasts have much lower skill, especially in the Upper Basin, and they are not incorporated in the CBRFC streamflow forecasts.
- A major research effort has ramped up in the last decade to advance sub-seasonal and seasonal forecasting.
- Sub-seasonal and seasonal forecasts for temperature are generally more skillful than forecasts for precipitation, and skill for both is generally higher for the Lower Basin than for the Upper Basin.
- For precipitation, the Climate Prediction Center's seasonal forecast skill in both basins has been positive for winter and spring, suggesting users should focus their forecast use on those seasons.
- There are other opportunities to better utilize the skill that does exist in sub-seasonal and seasonal climate forecasts, such as using them to “nudge” the streamflow forecast ensemble during post-processing.



Challenges and opportunities

Challenge

Limitations in our understanding of the connections between atmospheric and oceanic circulation patterns and processes, and Colorado River Basin precipitation variability in space and time, constrain the skill of climate forecast models in forecasting conditions for the basin.

Opportunities

- Support further research into these climate system dynamics to identify key patterns and variables.
- Support further research into better representing those key patterns and variables in dynamical climate forecast models and statistical forecast tools.

Challenge

The CBRFC and other streamflow forecasting units may not be able to capitalize on the skill that does exist in sub-seasonal and seasonal climate forecasts for the basin.

Opportunities

- Support ongoing CBRFC efforts to pilot the inclusion of sub-seasonal and seasonal forecasts in their forecast system.
- Support further research into post-processing of CBRFC forecasts to generate climate-forecast-informed, use-specific streamflow forecasts.

Challenge

The limited skill and probabilistic nature of climate forecasts may not mesh well with decision frameworks so water managers are unable to extract value from the forecast information.

Opportunities

- Continue to support engagement between water managers and CPC and other climate forecasters to facilitate shared understanding of decision needs and forecast capabilities.
- Study decision making by users and sectors that make better use of climate forecasts (e.g., crop futures traders), to assess transferability of tools and practices.
- Develop decision support tools that bridge climate forecasts to the water resource decision space.

Challenge

The skill of climate forecasts is highly variable over both space and time, complicating the consistent use of forecasts.

Opportunities

- Selectively consult forecasts during those seasons when they have shown the most skill for the basin.
- Support research to identify “forecasts of opportunity” specific to the basin, i.e., conditions of the ocean, atmosphere, and land surface during which forecasts are more likely to have skill and impact.

Chapter 8. Streamflow Forecasting

Key points

- Streamflow forecasts from the CBRFC are widely used by water managers in the basin and are critical inputs for Reclamation's operational models, including seasonal forecasts for use in 24MS and MTOM.
- Streamflow predictability at seasonal timescales in the Colorado River Basin arises primarily from the initial watershed moisture conditions, i.e., snowpack and soil moisture.
- While using different methods, the CBRFC and NRCS operational forecasts both effectively capitalize on this predictability, with relatively high skill for forecasts issued in late winter and spring for the coming runoff season.
- To improve streamflow forecasts within the current frameworks there are two main pathways: 1) improve estimates of initial watershed moisture conditions, and 2) improve basin-scale weather and climate forecasts and how they are used in streamflow forecasts.
- Improvements in quantifying watershed conditions can come through better meteorological analyses, more in situ observations of snowpack and soil moisture, increased use of remotely sensed observations, advances in calibration strategies, and advances in data assimilation techniques.
- Improvements in sub-seasonal and seasonal climate forecasts are being actively pursued by national modeling centers and the broader research community; targeted post-processing of climate forecasts can better leverage their current skill to inform seasonal streamflow forecasts.
- Skill in streamflow forecasts for year 2 and beyond is entirely dependent on skill in decadal climate forecasts, which exists to some degree for temperature but not for precipitation.
- Alternative forecast frameworks in which tasks are fully automated permit the use of a greater range of advanced methods and data. These frameworks have not yet been shown, however, to outperform the current operational forecasts.
- Many potential forecast improvement elements have been demonstrated in a research context; systematic testing to benchmark and combine multiple elements could add up to significant overall improvements in operational forecasts.



Challenges and opportunities

Challenge

The modeling advances over the last three decades and their demonstration in forecasting contexts have not altered the reliance of RFC operational practices on the legacy models. There is a clear scientific rationale for enhancing the physics of the legacy models in many forecast cases, yet implementing modeling advances faces major hurdles for operational flow prediction in both the current in-the-loop forecast paradigm and the over-the-loop workflow.

Opportunities

- Effective approaches for regional parameter estimation (calibration) in more complex watershed process models to enable model streamflow simulations on a par with the performance of current legacy models.
- Effective approaches for automated hydrologic data assimilation, to replace the many manual adjustments made by expert forecasters and enable skillful over-the-loop systems.
- Automated interoperability of water management decisions and river basin modeling systems, to replace the manual incorporation of management effects like releases and diversions.

Challenge

There is little question that more extensive monitoring of watershed conditions, either by direct or remote measurements, would benefit hydrologic forecasting. The benefits can arise in two ways: 1) improving real-time analyses that provide the initial conditions for forecasts, which matter most when those conditions provide most of the forecast signal, such as in late spring; and 2) improving model implementation by helping constrain model parameters and guide structural implementation of those parameters.

Opportunities

- Expansion of real time measurements of streamflow, snow water equivalent (SWE), soil moisture, and ET.
- Methodological research into how observations that are sparse or coarse (e.g., soil moisture) or collected as snapshots (e.g., ASO SWE) may be incorporated into a forecast workflow.
- Development of both real-time and multi-year (retrospective) records that provide a foundation for research and methodological verification.

Challenge

To open the door for adoption of more complex models, multi-faceted ensemble approaches, leveraging supercomputing, and other advancements in streamflow forecasting, the research and operational communities must develop effective automated hydrologic data assimilation methods.

Opportunity

- Experimentation and refinement of automated hydrologic data assimilation, particularly to enable over-the-loop prediction.

Challenge

It is clear that improved sub-seasonal (S2S) and seasonal climate predictions would have substantial benefit for mid-range hydrologic predictions, with a particular need for cool-season precipitation forecasts in the runoff-generating regions of the western U.S. Yet, S2S climate prediction has also long been a major scientific challenge, requiring large scale investments by the Earth system research community in improved global-scale observations, climate modeling, climate model data assimilation systems, and predictability studies.

Opportunity

- Invest in analysis and development of watershed-scale climate forecasts via both empirical and dynamical methods and sources as operational climate forecasting capabilities slowly evolve.

Challenge

The lack of a hydrologic forecasting testbed is a critical institutional gap. Support is needed to transition new research to operations for both the National Water Center and for the RFCs, and build the case for the viability of over-the-loop approaches.

Opportunity

- A testbed would support experimentation and systematic development of real-time forecast approaches, including new models, data assimilation techniques, post-processing approaches, model calibration techniques, climate and weather downscaling methods, verification and communication related to forecasts, and decision making.

Chapter 9. Historical Hydrology

Key points

- The observed historical streamflow record is used to generate ensembles of streamflow traces for input into system models for long-range planning, as well as to validate and calibrate paleohydrology and climate change-informed hydrology.
- Multiple methods have been used to generate Colorado River Basin streamflow traces for system analysis; each has advantages and limitations and none is a clear best choice for all applications.
- The index sequential method (ISM), which has been the most common method used in Reclamation system analyses for decades, has advantages but also significant limitations, most of which center on the fact that ISM traces do not deviate from the observed historical record.
- Stochastic alternatives to ISM have been used to produce ensembles of traces that maintain many characteristics of the historical record while offering novel ranges, durations, and frequencies of flows.
- Stochastic methods that are based on statistical summaries of the historical data, known as parametric methods, have the advantage of being able to generate values beyond the range of the observed record, but require assumptions about the underlying form of the population of streamflows.
- Stochastic methods that are based on sampling directly from the historical data, known as nonparametric methods, do not require assumptions about the underlying form of the population of streamflows but are sensitive to the number of observations from which to sample.
- Research trends are toward nonparametric methods of streamflow generation and toward hybrid methods that use historical hydrology with reconstructed tree-ring hydrology or climate change-informed hydrology.



Challenges and opportunities

Challenge

Identifying the most appropriate method of incorporating historical hydrology in long-term planning in the Colorado River Basin is a key challenge. The full, observed historical record, especially when used with ISM, likely does not represent future hydrologic risk, but it is challenging to completely replace it because there is no clear best alternative. While Reclamation's use of a segment of the observed hydrology (the Stress Test)

attempts to create a more realistic picture of risk, there is little guidance on which segments are most appropriate, and a shorter record reduces the range of hydrologic conditions available. Beyond ISM, there is much research but little consensus on alternative approaches to generating synthetic streamflow traces.

Opportunity

- One approach, informally suggested by Tarboton (pers. comm.), is that new streamflow generation models be tested against a comprehensive set of statistics. Extending that suggestion somewhat, a matrix could be established by Reclamation and basin stakeholders that identifies the most important features of synthetic traces and uses that matrix to guide research into new methods or to assess existing methods. Features in the matrix might include fidelity to particular historical statistics, ability to generate particular time steps, ability to simulate non-stationarity, ability to represent uncertainty, ease of implementation, ease of understanding, and robustness of inferences.

Challenge

One of the primary challenges facing water resources researchers and planners in applying the basin's historical time series is how to use it to generate streamflow traces that allow study of the non-stationary hydroclimate.

Opportunities

- Explore performing diagnostics on the parameters used in parametric stochastic streamflow studies in the Colorado River Basin to assess the dependencies between and among parameters and to assess the complexities involved in incorporating non-stationarity into them.
- Techniques for generating long-term streamflow sequences that blend historical observed hydrology with paleohydrology or climate change-informed hydrology (or both) offer substantial promise. The paleo record offers extremes, durations, and frequencies not seen in the observed record, and the climate change-informed hydrologies offer potentially altered climate patterns and regional shifts that are absent or undetectable from the observed and paleo records.
- A potentially useful effort might be to review approaches to other variables, and even other disciplines, for techniques that could be translated into streamflow synthesis techniques.

Chapter 10. Paleohydrology

Key points

- Tree-ring reconstructions of Colorado River streamflow extend the observed natural flow record up to 1200 years into the past and document a broader range of hydrologic variability and extremes than are contained in the observed records.
- Most critically, several paleodroughts prior to 1900 were more severe and sustained than the worst-case droughts since 1900.
- These “megadroughts” could recur in the future due to natural climate variability alone, but their recurrence risk is much increased by anthropogenic warming.
- The century-scale mean and variability of Colorado River Basin hydroclimate has not been stationary over time.
- The early 20th century high-flow years (1905–1930) may have been the wettest multi-decadal period in 500–1000 years.
- Methodological choices in the handling of the tree-ring data can influence the reconstructed flow values and metrics, such as the duration of droughts.
- Planning hydrologies derived from tree-ring paleohydrology can provide plausible stress tests that are more extreme than the observed hydrology, and have been used for that purpose in several recent planning studies in the basin.



Challenges and opportunities

Challenge

At present, only seven tree-ring site chronologies in the Upper Basin extend beyond 2005, so current streamflow reconstructions do not have the benefit of full calibration against the early 21st century dry period. Additionally, Reclamation’s ongoing revisions of natural flow estimates may, cumulatively, substantially revise the target hydrology for tree-ring flow reconstructions.

Opportunities

- Develop new or updated tree-ring site chronologies that can be included in the calibration of any forthcoming streamflow reconstructions.
- Consider recalibration of, as well as assessment of the sensitivity of, the tree-ring flow reconstructions to the revised natural flows.

- Generate new, targeted reconstructions for the key water supply regions of the Upper Basin like the ongoing project funded by the USGS Southwest Climate Adaptation Science Center, in collaboration with basin water managers.

Challenge

Key to applications of paleohydrology to future climate scenarios is understanding how modes of natural variability itself will change over the coming decades. It is unclear which methods of blending paleohydrology data and climate projections have the most robust physical foundation, and more work is needed to examine the issue of persistence in streamflow reconstructions and to determine its source.

Opportunity

- Develop plausible scenarios and characteristics of future basin drought over the next several decades through integration of paleohydrology data and climate projections. Some of this work is underway, as described above.

Challenge

Existing tree-ring reconstructions of annual and growing-season temperature for the basin are not nearly as skillful as reconstructions of precipitation and streamflow, limiting our ability to tease apart the drivers of past low-flow periods and place the recent warming trend in context.

Opportunity

- Renew efforts to develop a robust reconstruction of past basin temperatures, building on current investigations using bristlecone pine, plus updating and re-measuring other collections of trees that are limited in growth by temperature.

Chapter 11. Climate Change-Informed Hydrology

Key points

- Climate change-informed hydrology is increasingly used in basin planning studies to complement other long-range hydrologic information.
- Most approaches to developing this information begin with global climate models (GCMs) driven by one of several emissions scenarios; the approaches incorporate multiple processing steps, with corresponding methodological choices that each have implications for the final output and its uncertainty.
- GCMs are the best tools we have for exploring and quantifying physically plausible future climate changes at global to sub-continental scales. They have deficiencies in representing some key climate system features relevant to basin-scale climate, as well as reproducing historical basin-scale climate patterns themselves.
- Downscaling methods make GCM output more usable for finer-scale hydrologic modeling, such as projections of future streamflows. Downscaled projections are not necessarily more accurate than the underlying GCM output in depicting future climate change.
- Further warming is projected by all GCMs to continue in the basin as a consequence of continuing greenhouse gas emissions; basin temperatures are projected to rise by 2.5°F–6.5°F by mid-century relative to the late 20th century average.
- The direction of future precipitation change for the basin is much less certain than temperature change. The GCMs show some overall tendency toward increasing annual precipitation in the northern parts of the Upper Basin, and toward decreasing precipitation from the San Juan Basin south through the Lower Basin.
- The projected trends in precipitation are relatively small compared to the high year-to-year natural, or internal, variability in precipitation. Most GCMs project increased precipitation variability in the future.
- Mainly due to the pervasive effects of warming temperatures on the water cycle, nearly all of the many datasets of climate change-informed hydrology and related studies show a strong tendency toward lower annual runoff volumes in the Upper Basin and the Lower Basin, as well as reduced spring snowpack and earlier runoff.
- The overall spread of potential future hydroclimatic changes for the basin, as depicted across the GCM-driven projections, has not been reduced over the past decade and may not be appreciably reduced by



forthcoming data and methods, not least because much of the spread is due to unpredictable natural climate variability.

Challenges and opportunities

Challenge

GCM disagreements in changes of key climate variables: 1) GCMs do not agree on the magnitude of warming to expect globally, or in the basin, for a given emissions scenario-timeframe combination; 2) GCMs do not agree on the direction and magnitude of annual precipitation change for the basin. Based on past history, further improvements in GCMs (e.g., better resolution of CMIP6 GCMs) will likely only slowly reduce these disagreements.

Opportunities

- Pursue additional guidance beyond the GCM ensemble regarding changes in these uncertain variables, e.g., recent observed trends, climate theory, and expert opinion (e.g., surveys of researchers).
- Identify specific hydroclimate conditions, events, and sequences that lead to vulnerability; there may be greater consensus among the GCMs regarding these than in the changes in annual or seasonal average precipitation, for example.

Challenge

Due to GCM uncertainty and other factors, the range of projected future outcomes for basin hydrology (e.g., change in annual runoff volume at Lees Ferry) from GCM-based ensembles is very broad, and most planning decisions cannot address the full range of potential future conditions without incurring regrets from under- or over-preparation.

Opportunities

- Methods are available (e.g., scenario development, hydrologic storylines) to at least reduce the number of traces from the ensemble, improving their tractability for planning, and potentially identifying more physically plausible and likely outcomes.
- Alternative planning paradigms may be more appropriate for decision making under deep uncertainty. In planning, emphasize those outcomes associated with greater vulnerability and impacts, i.e., drier projections.

Challenge

GCM resolution, while improving, is still coarser than that required for realistic modeling of basin hydrology and system modeling, requiring the application of downscaling methods.

Opportunity

- The HighResMIP experiment within CMIP6 will soon make available an ensemble of GCM projections at 25–50 km resolution. This is still coarser than the resolution optimal for hydrologic modeling but will provide a useful test of what added value can be expected from high-resolution GCMs.

Challenge

Statistically downscaled projection datasets, which dominate applications of regional climate data in water supply assessments, are perfectly adequate as sequences to input in hydrology models, but they add little to our physical understanding of future changes beyond what the GCMs can tell us. The very high resolution of these datasets (1–12 km) can also mislead users as to their accuracy and added value.

Opportunity

- For water supply assessments, look to dynamically downscaled or hybrid methods and datasets (e.g., NA-CORDEX, ICAR, En-GARD) for more physically oriented guidance that can provide context for statistically downscaled datasets, or replace them.

Challenge

The sources of uncertainty and differences in climate change-informed hydrology for the basin have been identified and explored to varying degrees, but not fully examined, including the underlying methodological choices. Thus, data users have incomplete information about uncertainty, and may not be aware of the subjective choices underlying particular results of hydrologic assessments.

Opportunities


- Support comprehensive evaluations of the differences stemming from downscaling methods, bias-correction methods, and hydrologic models.
- Provide visualization tools of future climate and hydrology that are not limited to a single dataset and allow the users to toggle between datasets to clearly see commonalities and differences.

Challenge

Any given ensemble of climate change-informed hydrology (e.g., CMIP5 BCSD) is a complex dataset that is challenging to obtain, analyze, and interpret; the increasing proliferation of similar datasets and their respective underlying methodological approaches can be bewildering to even sophisticated users.

Opportunities

- For both researchers and practitioners, support efforts to provide guidance on the appropriate use of existing datasets, e.g., Vano et al. (2018), and WUCA training workshops.
- Develop and disseminate new methods and datasets only when there is a compelling use case and clear added value over existing datasets.

The background of the page is an aerial photograph of a rugged, mountainous landscape. The terrain is characterized by deep, winding canyons and ridges, with a river or stream flowing through a valley. The colors are primarily earthy browns, tans, and greys, with some patches of green vegetation. The lighting creates strong shadows, emphasizing the topography.

Volume I

Background and Context

Chapter 1. Introduction

Chapter 2. Current Understanding of Colorado River Basin Climate and Hydrology

Chapter 3. Primary Planning Tools

Volume I of the Colorado River Basin State of the Science report provides important background and context for considering the different datasets, models, and tools described in the subsequent volumes and chapters. Chapter 1 succinctly lays out the need for the report as well as its objectives, intended audience, approach, and organization. It also contains a primer on sources of uncertainty to help readers navigate more focused discussions of uncertainty in later chapters.

Chapter 2 is a technical report unto itself; it describes what is known about the fundamental features of the Colorado River Basin's hydroclimate, their spatial and temporal variability, and the mechanisms behind that variability. This knowledge base is dependent on the primary datasets and models described in Volume II (Chapters 4, 5, and 6) while also informing the productive application of those data and models, and similarly it underpins the application of the weather, climate, and streamflow forecasting methods described in Volume III (Chapters 7 & 8). The chapter concludes with a detailed discussion of recent trends in basin hydroclimate and their likely causes, which provides critical context for the long-term planning datasets described in Volume IV (Chapters 9–11).

Chapter 3 provides a detailed overview of the three primary Reclamation operations and planning models that support basin decision making. It describes the underlying configurations, assumptions, and applications of the three models. The chapter details how these models use observational data, streamflow forecasts, and planning hydrologies as a prelude to the discussion of those inputs in subsequent chapters.



Chapter 1

Introduction

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Western Water Assessment, University of
Colorado Boulder.

1.1 Background and need

The Colorado River Basin is a vital source of water, ecosystem services, hydropower, recreation, and other amenities for the seven basin states (Colorado, Wyoming, Utah, New Mexico, Arizona, Nevada, and California), at least 22 federally recognized tribes, and the Republic of Mexico (Figure 1.1). The Colorado River system is managed and operated in accordance with the Law of the River, which consists of compacts, treaties, federal laws, regulations, contracts, and court decisions and decrees.

There is an increasing imbalance between supply and demand in the basin. Water use, including consumptive use, within the basin has steadily increased over time and, when combined with deliveries to Mexico, is now approaching the average historical water supply (Figure 1.2). The average conditions, over time and across the basin, suggest a (barely) sufficient supply and, by smoothing out the variability, mask existing and prospective shortages.

Since 2000, the basin has experienced an extended dry period in which the average annual water supply has been 18% lower than the historical average. The enormous storage capacity of the system's reservoirs (about 60 million acre-feet), nearly full at the beginning of the dry period, combined with voluntary conservation has permitted full deliveries of water to the Lower Basin states through this period, with only local shortages to uses in Upper Basin states. But the cumulative streamflow deficit of about 40 million acre-feet (maf) since 2000 has contributed to the depletion of system storage to about 45% of capacity.

The depleted state of system reservoirs leaves the system vulnerable; the water surface elevation of Lake Mead has hovered around the upper thresholds (1075' and 1090') for imposing curtailments on Lower Basin states under the 2007 Interim Guidelines and the 2019 Drought Contingency Plan.

This recent drought, along with the increasing recognition that rising temperatures impact the hydrology of the basin, has led to further concerns about the long-term reliability of basin water supplies. Warming temperatures observed across the basin in the last few decades have discernibly impacted snowpacks, melt and runoff timing, runoff efficiency, and total basin runoff. It is unclear whether the period of below-normal precipitation since 2000 is indicative of future precipitation, but unless average basin precipitation increases substantially, system runoff and water supply are expected to decline over the next several decades due to warming alone.

Law of the River

See Reclamation's website for links to many of the relevant documents.

Link:

<https://www.usbr.gov/lc/region/pao/lawofrvr.html>

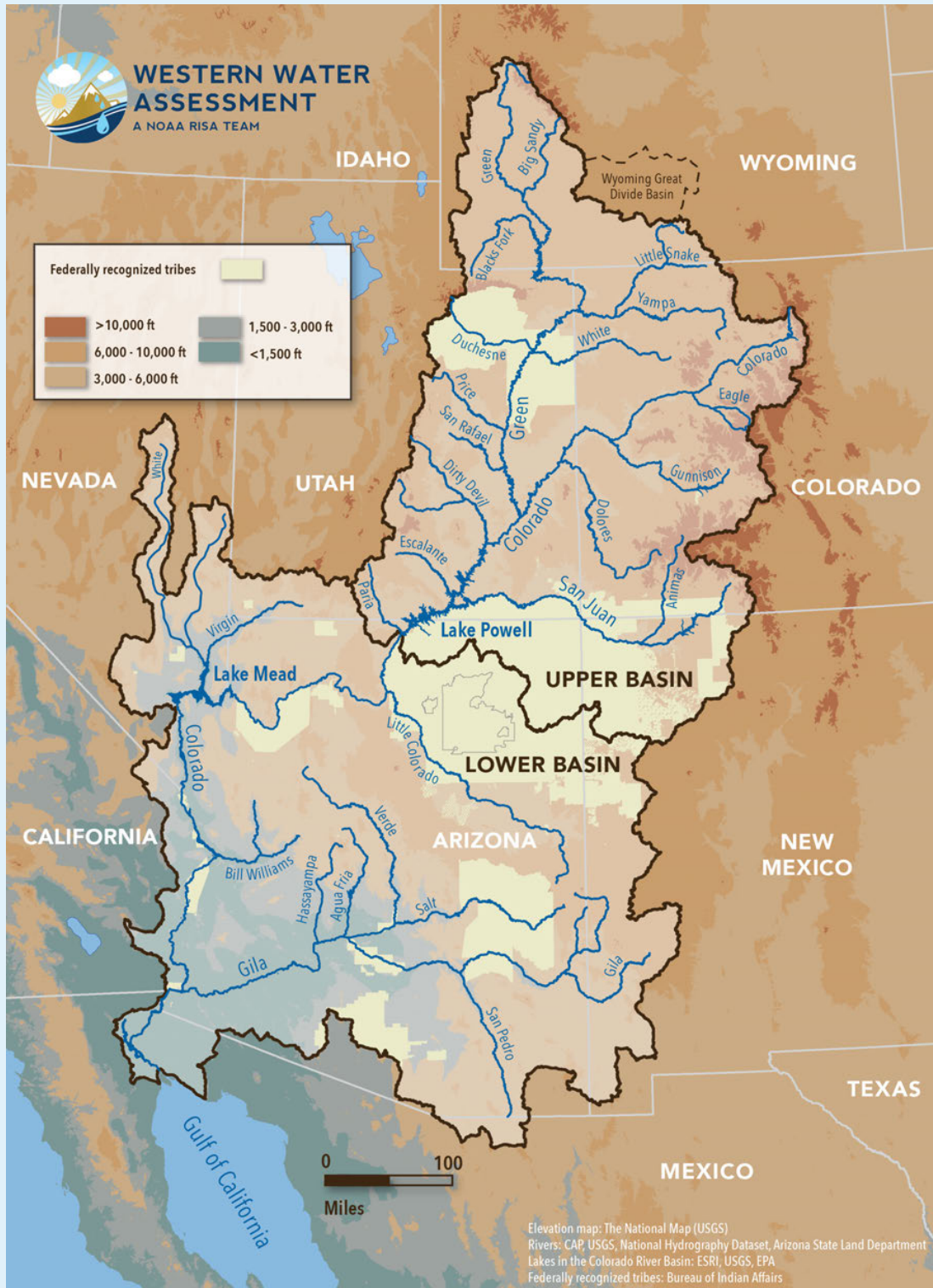


Figure 1.1

Geographic setting of the Colorado River Basin. Upper Basin: portions of the basin that lie in Colorado, Utah, Wyoming, New Mexico, and Arizona that are tributary to the river upstream of the Colorado River Compact point at Lee Ferry, Arizona. Lower Basin: portions of the basin in Arizona, California, Nevada, and New Mexico that are downstream of Lee Ferry.

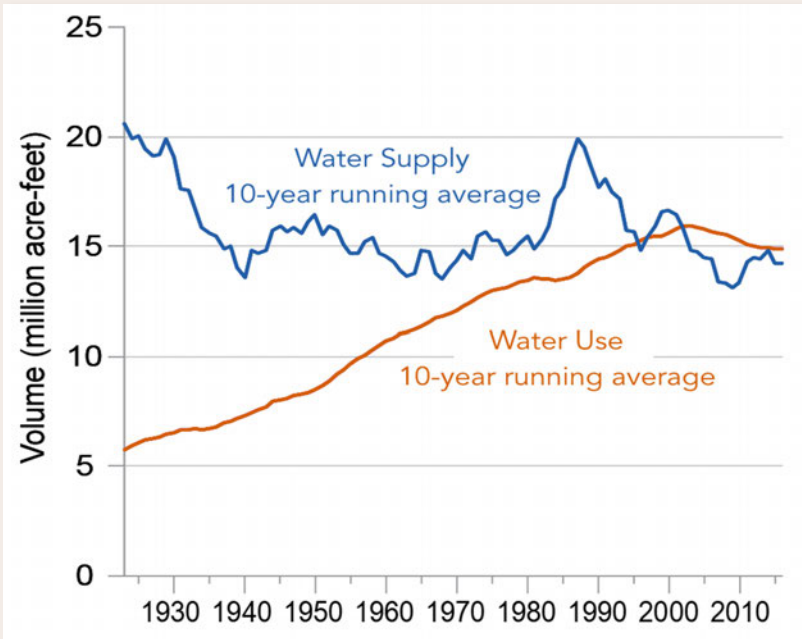


Figure 1.2

Historical water supply and consumptive water use for the Colorado River Basin, as aggregated at Imperial Dam, from 1922 to 2016, smoothed with a 10-year running average. Since 2000, water use has exceeded water supply on a 10-year basis, as well as in most individual years. (Source: USGCRP 2018, revised from Reclamation 2012e)

Water resource managers in the basin have long relied on short-term (1 month to 2 years) forecasts of system conditions to guide operations and other decision making. Recently, the U.S. Bureau of Reclamation (hereinafter “Reclamation”) has instituted mid-term probabilistic forecasts (2 to 5 years) to bridge short-term forecasts with longer-term planning projections. When the system is close to critical operational thresholds, such as the 1075’ and 1090’ levels in Lake Mead, the need for accurate and actionable short-to-mid-term forecasts of system conditions becomes even more critical.

Until recently, long-term water planning (5 to 50 years) in the basin was based on the historical hydrologic record under the assumption of hydroclimatic stationarity, that is, that the historical average and variability would remain stable. That assumption was first challenged several decades ago by tree-ring records showing the instability of century-scale hydroclimate in the basin, and has become even less tenable due to climate change (Milly et al. 2008; 2015). When developing the 2007 Interim Guidelines, Reclamation, recognizing the limitations of the conventional assumption of stationarity, used tree-ring reconstructed, pre-historic flows to provide a broader view of flow variability (Reclamation 2007b), and also surveyed the state of knowledge regarding the potential impact of climate change on water resources in the basin (Reclamation 2007c). Since that time, climate model projections have played larger roles in informing the hydrologic traces in Reclamation planning studies (Reclamation 2012e). Reclamation’s experience, and that of other water agencies working with climate model data, has revealed considerable challenges in both

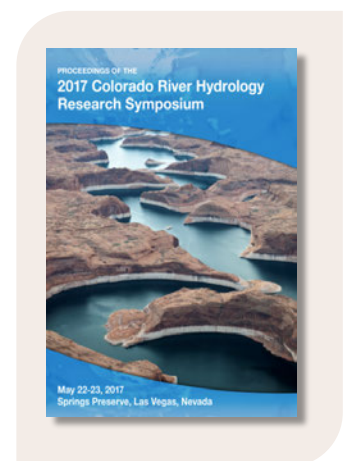
translating global climate projections to changes in the hydrology of the Colorado River Basin and in interpreting the system impacts associated with those changes given the uncertainties in the data and models.

The past decade has seen dozens of new research efforts aimed at better understanding the climate and hydrology of the Colorado River Basin, and at refining the data and models used to guide basin management and planning. There have been parallel efforts to explore new approaches to planning and decision making under uncertainty. Many of these efforts have been conducted by, or with funding from, Reclamation and other basin water agencies. Many other research studies, while not explicitly guided by the needs of basin water managers, can still provide relevant information and insight. Given this rapidly expanding scientific knowledge base, the increasing complexity of the data and models used to operationalize that knowledge, and the growing uncertainties about the hydroclimatic future, basin stakeholders have recognized the importance of reassessing the scientific and technical basis for management and planning. The impending formal review of the 2007 Interim Guidelines, which must begin in 2020 (U.S. Secretary of the Interior 2007), and the potential renegotiation of those guidelines, has created additional impetus for such a reassessment.

In May, 2017, the Southern Nevada Water Authority hosted a conference, the Colorado River Hydrology Research Symposium (Cawthorne 2017), to give water resource practitioners and researchers an opportunity to exchange information about operational practices and research initiatives, with a focus on opportunities to improve inputs to existing basin planning tools and to enhance the utility of those tools. One outcome of that symposium was recognition that a document that synthesized the current research and assessed it in the context of the primary planning processes was necessary.

1.2 Objectives and approach

The intention of this report is to assess scientific knowledge and technical practice in a systematic way, across the multiple timescales and the diverse data and models used to inform management and planning in the basin. It describes the concepts, methods, models, and datasets that currently contribute to Reclamation's and other stakeholders' operations and planning, as well as knowledge gaps, uncertainties, and future challenges and opportunities. No new research or quantitative analyses were performed for this report beyond the basic characterization of existing datasets.



Objectives

By synthesizing the state of the science in the Colorado River Basin regarding climate and hydrology, the report seeks to establish a broadly shared understanding that can guide the strategic integration of new research into practice. The ultimate goal of that integration, and therefore of this report, is to facilitate more accurate short- and mid-term forecasts, and more meaningful long-term projections, of basin hydroclimate and system conditions.

The specific objectives of this report include the following:

- Synthesize recent findings that can inform forecasts (short-term and mid-term) and projections (long-term) of hydroclimate and system conditions.
- Convey the knowledge gaps and uncertainties associated with each area of the science and technical practice, as well as with key datasets and models.
- Prompt research ideas and inform research priorities by describing opportunities for closing knowledge gaps.
- Inform the scientific community about Reclamation models, how they support operations and planning, and related research needs.
- Provide a broadly accepted foundation of scientific and technical issues on which to enter the formal review and potential renegotiation of the Interim Guidelines.

Sources

This report draws from over 700 primary sources, mainly peer-reviewed research articles published in academic journals, as well as agency studies, reports, analyses, and other sources. It builds on prior planning studies, research syntheses, and information needs assessments that have focused on the Colorado River Basin and water resources management that are listed in Table 1.1.

Audience

This report was written to be a clear and useful reference for readers who come to it with a moderate level of scientific and technical understanding of hydrology, though much of the text is fully accessible to any reader. The audience for the report includes water resource engineers and analysts who routinely work with inputs to, or outputs from, Reclamation models or who otherwise engage with water operations and planning in the basin; decision makers who will prescribe changes to operations, plans, and policies, and could benefit from better understanding of the science that informs these activities; research program managers seeking insights on high impact priorities to promote; and researchers who could benefit from better understanding of the planning and decision context in the basin. The report is also intended to inform the funding and production of research

that effectively supports basin water management activities, and is therefore also aimed at the broader community of water interests in the basin.

Table 1.1

Planning studies, research syntheses, and information needs assessments referenced in this report.

Document	Year	Geographic scope	Reference
Planning studies conducted by Reclamation or basin stakeholders			
Final EIS—Colorado River Interim Guidelines for Lower Basin Shortages and Coordinated Operations for Lake Powell and Lake Mead, Appendices N and U	2007	Colorado River Basin	Reclamation (2007b; 2007c)
Colorado River Basin Supply and Demand Study	2012	Colorado River Basin	Reclamation (2012e)
Colorado River Water Availability Study	2012	Major Colorado River tributary basins within the state of Colorado	Colorado Water Conservation Board (2012)
SECURE Water Act report	2016	Western U.S.	Reclamation (2016)
Colorado River Basin Ten Tribes Partnership Tribal Water Study	2018	Colorado River Basin	Reclamation (2018)
Climate change assessments that cover part or all of the Colorado River Basin			
Climate Change in Colorado	2008	Colorado	Ray et al. (2008)
Joint Front Range Climate Change Vulnerability Study	2012	Colorado	Woodbury et al. (2012)
Assessment of Climate Change in the Southwest United States	2013	Southwestern U.S.	Garfin et al. (2013)
Climate Change in Colorado	2014	Colorado	Lukas et al. (2014)
Fourth National Climate Assessment, Volume I	2017	U.S.	US Global Change Research Program (2017)
Fourth National Climate Assessment, Volume II, Chapter 25	2018	Southwestern U.S.	Gonzalez et al. (2018)
Stakeholder needs assessments for climate information			
Options for Improving Climate Modeling to Assist Water Utility Planning for Climate Change	2009	U.S.	Barsugli et al. (2009)
Addressing Climate Change in Long-Term Water Resources Planning and Management: User Needs for Improving Tools and Information	2011	U.S.	Brekke (2011)
Short-Term Water Management Decisions: User Needs for Improved Climate, Weather, and Hydrologic Information	2013	U.S.	Raff et al. (2013)

1.3 Organization

The organization of the report centers on the three main Reclamation operations and planning models for the basin and the respective timescales those models are designed to inform. The models are:

- 24-Month Study Model (24MS)—short term (current month to 24 to 36 months in the future)
- Mid-Term Probabilistic Operations Model (MTOM)—mid-term (current month to 2 to 5 years in the future)
- Colorado River Simulation System (CRSS)—long term (5 to 50 years)

In general, operational and planning decisions by Reclamation or basin stakeholders use information from the four categories of models or data listed below.

- I. **System Models.** The three primary Reclamation models listed above, and equivalent models built and used by other organizations. They use as inputs the data from categories III and IV, and are also calibrated with data from category II.
- II. **Primary data and models.** Observations, estimates, or simulations of climate and hydrologic conditions that are relevant across all time scales. They are used to calibrate, provide inputs to, and validate models and analyses in categories I, III, and IV.
- III. **Short- and mid-term forecast tools.** Models and methods for forecasting weather, climate, and streamflow as the basis for short-to-mid-term operations.
- IV. **Long-term planning hydrology.** Data and models (historically-based, paleo-reconstructed, and climate change-informed) used to represent past and current variability, and to project long-term future conditions for planning purposes.

This report is organized into four volumes (I–IV) corresponding to these categories, reflecting the flow of information through the chain of models and data. While that flow actually culminates with the Reclamation system models, those models are described early in the report (Volume I, Chapter 3) to set the stage for consideration of the manifold inputs to those models.

In Chapters 3 through 11, the text describes the following for each type of model or data:

- Importance to the chain of models and data, and thus to basin operations and planning
- The specific data and methods currently used in the Reclamation models, and how they compare with other data and methods
- Recent or ongoing efforts at improvement in this area
- Key challenges, knowledge gaps, and uncertainties that remain
- Opportunities for further progress

1.4 Topics beyond the scope of this report

This report does not evaluate current basin operations and policy or provide recommendations. It also does not address ecosystem processes except as they affect water supply, nor does it cover water quality concerns in any detail.

Water use is obviously a critical component of the system water balance in the Colorado River Basin. Specific aspects of water use are briefly addressed in this report: the representation of consumptive water uses and losses in the Reclamation system models (Chapter 3); methods for measuring and monitoring water uses and losses (Chapter 5); and the effects of climate change on consumptive use (Chapter 11). Other sections may include discussions of data, tools, and concepts that, while oriented toward water supply, are relevant to the quantification of current consumptive uses and losses and the forecasting of future water demand. But a comprehensive treatment of the scientific and technical issues surrounding water use in the basin is beyond the scope of this report. The state of monitoring and forecasting water use in the basin for planning purposes is described in Technical Report C of the Colorado River Basin Water Supply and Demand Study (Reclamation 2012d).



Sources of uncertainty in modeling natural systems

The uncertainties in hydroclimate forecasts and projections, and therefore in water supply expectations, present tantalizing research questions for scientists but are a source of frustration for water resource practitioners charged with providing a reliable water supply. Given the stakes involved, it is reasonable that Colorado River Basin planners and managers desire greater certainty in water supply forecasts and long-term projections; they need some sense of the likelihood of hydrologic shifts, especially shifts to the dry side.

Uncertainty stems from either randomness in the behavior of the system being modeled (aleatory uncertainty) or incomplete knowledge of the system (epistemic uncertainty). The aleatory uncertainty in hydroclimate processes is effectively synonymous with natural variability and, as such, can't be reduced by more research or computing power or data collection. Just as we cannot buy down the uncertainty in a coin flip, we cannot buy down aleatory uncertainty in hydroclimate processes. However, aleatory uncertainty as manifested in variability is an intrinsic element of hydrologic systems, so its conceptual and practical nature is well understood by water resource managers and stakeholders.

Epistemic uncertainty, on the other hand, can be chipped away at by improving our understanding, computing power, and data collection. There is epistemic uncertainty about aleatory uncertainty (variability) which frequently will be reduced simply by making more observations. For example, the exceptional nature of the wet period at the beginning of the 20th century was revealed over time as the observed records of precipitation and streamflow became longer. There are several general types of epistemic uncertainty in modeling natural systems, illustrated in Figure 1.3 and described below:

- **Conceptual.** Uncertainty that comes from incomplete understanding of the system to be modeled, so that relevant variables and processes are not represented in the model or the underlying dependencies between and among processes and variables is poorly understood.
- **Structural.** Uncertainty that comes from inadequate specification of the underlying physics and other physical relationships in the model, or the imperfect fit of a statistical model. Approximation or simplification of processes over time and space is another source of structural uncertainty.
- **Parameter.** Uncertainty that comes from errors in specifying model parameters—usually these are fixed coefficients or terms based on observations. Aggregation or simplification of inputs over time and space is another source of parameter uncertainty.
- **Data.** Uncertainty that arises from limitations in observing systems and measurement techniques. Data uncertainty is fundamental because it confounds our conceptual and quantitative understanding of natural systems. Calibration of model parameters against imperfect data contributes to parameter uncertainty.
- **Initial conditions.** Uncertainty that comes from imperfectly capturing the state of the system that begins a model simulation; it includes measurement error, and even more so, uncertainties related to the spatial and temporal interpolation between observations.

Uncertainties accumulate such that the combined uncertainty in the ultimate planning model output is much larger than the uncertainty at any intermediate step; however, because of interdependencies, the combined uncertainty isn't a simple addition. Ultimately, depending on the variable and time scale of interest, the combined epistemic uncertainties may be matched or exceeded by that stemming from the natural variability of the Colorado River Basin.

This report summarizes the current understanding in the research community about the uncertainties in hydroclimate analyses. However, the full range of uncertainty in future system outcomes, as it applies to the Colorado River Basin, also includes future land use, future water demand, and the future state of institutions, economies, technologies, and policies that influence and constrain water demand and allocation. Water resource practitioners in the basin are trying to make the best decisions possible about infrastructure, operations, and demand management given the uncertainty in future water supply. Studies to support decision making in this new environment are beginning to explore alternative analytical approaches that address the lack of information about the future by first evaluating system sensitivities, vulnerabilities, or failure modes. This emerging paradigm is reflected in the “decision making under deep uncertainty” (DMDU) movement. DMDU often uses computationally intensive methods, testing a system's vulnerability to a range of possible futures under multiple policy options, to formulate robust decisions. It is possible that approaches to decision making such as these may be more likely to benefit management and planning than efforts to reduce some of the epistemic uncertainties, but discussion and evaluation of the approaches and the trade-offs is beyond the scope of this report.

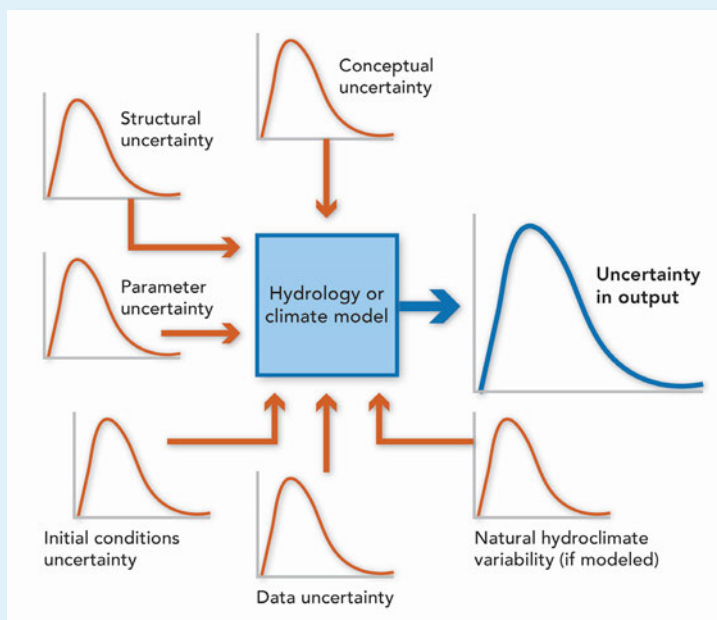


Figure 1.3

Sources of uncertainty in modeling natural systems. The figure shows hypothetical probability density functions combining to representing the overall uncertainty in model output.



Chapter 2

Current Understanding of Colorado River Basin Climate and Hydrology

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Key points

- On average, about 170 million acre-feet (maf) of precipitation falls over the Colorado River Basin annually, but only about 10% (17 maf) becomes natural streamflow available for use.
- The Upper Basin contributes the vast majority, about 92%, of the total basin natural streamflow as measured at Imperial Dam.
- Elevation dramatically shapes the amount of precipitation and its relative contribution to runoff, so that 85% of annual runoff comes from the 15% of the basin's area that is located in the mountain headwaters.
- The position and activity of the mid-latitude storm track from October through May is the critical climatic driver of annual precipitation in the basin's headwaters.
- Snowmelt is the primary source of annual runoff from those mountain headwaters, as reflected in the prominent late-spring peak in the annual hydrograph.
- Year-to-year variability in runoff is high and is mainly driven by variability in precipitation; decadal and multi-decadal variability in precipitation and in runoff is also present but no consistent cycles have been identified.
- The predictability that does exist at shorter time scales (up to 1 year) comes mainly from the El Niño-Southern Oscillation (ENSO); the ENSO signal is generally weak in the Upper Basin but stronger in the Lower Basin.
- Predictability at decadal and longer time scales using longer-lived climate phenomena (e.g., Atlantic Multidecadal Oscillation, Pacific Decadal Oscillation, etc.) has proven elusive.
- The period since 2000 has been unusually drought-prone, but even more severe and sustained droughts occurred before 1900.
- There has been a substantial warming trend over the past 40 years; the period since 2000 has been about 2°F warmer than the 20th-century average, and likely warmer than at any time in the past 2000 years.
- Decreases in spring snowpack and shifts to earlier runoff timing in many parts of the Upper Basin, as well as decreases in annual Colorado River flows at Lees Ferry, Arizona, have occurred in recent decades. These changes in hydrology can be linked, at least in part, to the warming trend.

2.1 Introduction

Describing the spatial and temporal variability of the Colorado River Basin's hydroclimate, and recent trends in hydroclimate, can help frame expectations of future basin hydrology even before consulting the tools explicitly designed for forecasting and projection. It also provides context for the different datasets and modeling platforms that are considered in

much greater detail in later chapters. Understanding the physical mechanisms that drive basin climate and hydrology, and their links with the global climate system, can also help identify and understand issues with the output of both hydrology models (Chapter 6) and global climate models (Chapter 11).

2.2 Overview of the basin

Within its 240,000 square miles, the Colorado River Basin hosts an extraordinary diversity of hydroclimatic environments across an elevation range from sea level to over 14,000' (4300 m). Some of the mountain headwaters receive over 60" of precipitation per year and have annual average temperatures well below freezing, while the driest desert valleys see 4" of precipitation per year and maximum daily temperatures over 120°F (Figure 2.1). Due to the rugged topography, abrupt climatic gradients are common, with annual precipitation increasing by a factor of up to 5 over less than 20 miles from base to summit of mountain ranges and high plateaus.

The large majority of the basin has an arid or semi-arid climate—that is, under 20" of annual precipitation—and produces little or no runoff. The precipitation returns to the atmosphere as water vapor before reaching a stream by evaporating from soil and open water, sublimating from the snowpack, or transpiring from natural vegetation and crops—processes collectively known as evapotranspiration, or ET. The relatively spatially restricted mountain areas at high elevations, that are wet and cold enough to allow a seasonal snowpack to accumulate, produce a highly disproportionate amount of total basin runoff; about 85% of the average annual runoff is contributed by 15% of the surface area of the basin (Christensen and Lettenmaier 2007). The vast majority of these highly productive headwaters are located in the Upper Basin, primarily in western Colorado, and also in southwestern Wyoming and northeastern Utah. Accordingly, the Upper Basin accounts for, on average, 92% of the total natural streamflow as measured at Imperial Dam (Table 2.1).

Runoff efficiency is highest in the mountainous northern and eastern sub-basins of the Upper Basin (Figure 2.1), averaging 25–30% averaged across those basins. The highest elevation catchments within those sub-basins may see runoff efficiencies of 40–60%. Averaged across the Upper Basin, runoff efficiency is about 16%, and for the entire basin, it is only around 10% (Table 2.1). Both values are comparable to the runoff efficiency estimated for the Upper Missouri basin (about 12%; McCabe and Wolock 2019), but far lower than the runoff efficiency for the Columbia River Basin and the river basins that head in California's Sierra Nevada (40–50%; Das et al. 2011). Significantly, basins with relatively low runoff efficiency have higher

Colorado River at Lees Ferry

The USGS gage at Lees Ferry, Arizona, number 09380000, records Colorado River streamflows immediately above the mouth of the Paria River, 16 miles downstream from Glen Canyon Dam, and 1 mile above the Colorado River Compact point at Lee Ferry, Arizona.

sensitivity of runoff to variability and changes in both temperature and precipitation (Das et al. 2011).

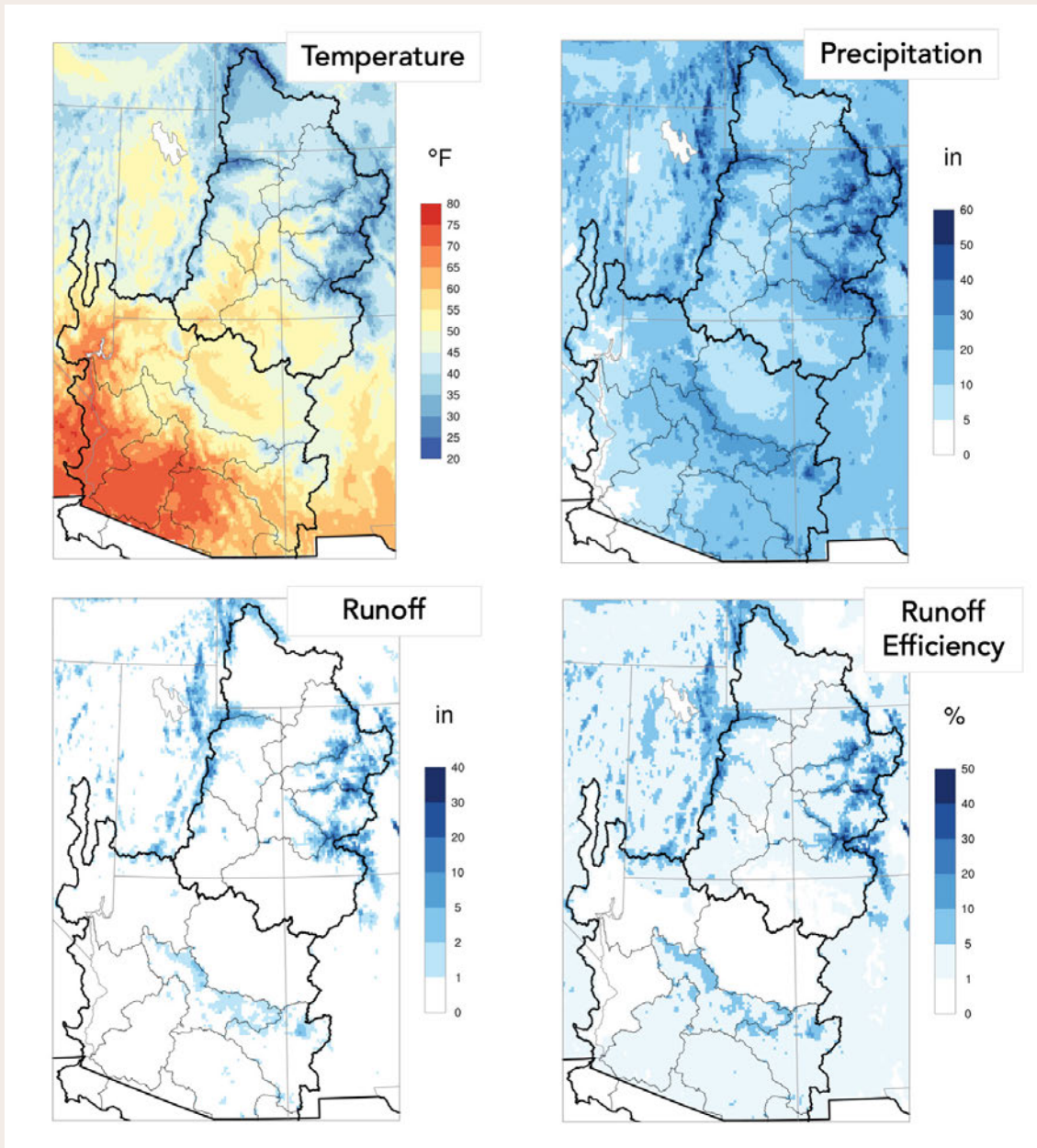


Figure 2.1

Colorado River Basin observed average annual temperature (upper left), observed average annual precipitation (upper right), modeled average annual runoff (lower left) and modeled annual average runoff efficiency, over the 1981-2010 period. (Data: Livneh et al. 2013; the average temperature and precipitation patterns shown are nearly identical to those seen in the PRISM and gridMet datasets. See Chapter 4 for discussion of these and other gridded climate datasets.)

Table 2.1

Long-term (1906–2017) average water-year natural runoff, average water-year precipitation, and calculated runoff efficiency for sub-basins of the Colorado River. (Data: Runoff from Reclamation, after Prairie and Callejo (2005) except for Gila River; Gila River from Lukas, Wade, and Rajagopalan (2013); Precipitation from NOAA NCEI).

Basin or Sub-basin (gage)	Natural Streamflow (maf)	Proportion of Colorado River at Imperial Runoff (%)	Precipitation (maf)	Runoff Efficiency (%)
Green River (nr Green River, UT)	5.4	34%	92 maf Upper Basin Total	16%
Colorado River (nr Cisco, UT)	6.8	42%		
San Juan River (nr Bluff, UT)	2.1	13%		
Total Upper Basin (Colorado River at Lees Ferry)	14.8	92%		
Inflows between Powell and Mead	0.8	5%	78 maf Lower Basin Total (includes Gila River Basin)	3%
Inflows between Mead and Imperial Dam	0.4	3%		
Total inflows between Powell and Imperial Dam	1.3	8%		
Total Colorado River above Imperial Dam	16.1	100%		
Gila River (nr Dome, AZ at mouth)	1.1			
Total Colorado River at Yuma, AZ	17.2		170 maf	10%

Because the vast majority of basin-wide runoff comes from mountain headwaters that are mainly restricted to the periphery of the Upper Basin, the assessment of past variability and likely future changes in Colorado River hydrology will be more meaningful if focused on these headwaters areas. However, these critical mountain areas have fewer and shorter observational records, and are more difficult to represent in models than the more extensive low- and mid-elevation regions of the basin.

2.3 Moisture sources, storm tracks, and seasonality of precipitation

The broad spatial patterns of annual precipitation and runoff in the Colorado River Basin described above, while largely driven by topography, also result from the dynamic motions of the atmosphere over the basin, including upper-level winds, storm tracks, and convergence of air masses. These atmospheric dynamics, while very chaotic on shorter time scales (i.e., weather), have some regularity on seasonal time scales. Accordingly, they help create distinct patterns of seasonality in precipitation across the basin (Figure 2.2), as well as some of the broad gradients in average annual precipitation (Sheppard et al. 2002).

During the cool season, the primary moisture source for precipitation over the basin is the Pacific Ocean. In summer, the Gulf of California is the main source of moisture for the Lower Basin (Jana et al. 2018). In spring and summer, the Gulf of Mexico becomes a secondary moisture source for the far eastern portions of the basin. Also during spring and summer, a considerable fraction of precipitation across the basin is “recycled”—derived from moisture that has evaporated from the land surface (Jana et al. 2018).

Starting off the water year, October is usually a transitional month as the atmospheric patterns characteristic of winter emerge. Rapid cooling in the Arctic drives increasingly large north-south contrasts in temperature between the tropics and the polar regions. This temperature contrast both strengthens the prevailing westerly winds and promotes the development of mid-latitude cyclonic storms and other disturbances. The core of the upper-level westerly winds, the polar jet stream, also shifts southward at this time. Storms preferentially form along the jet stream’s path, and then tend to follow that path eastward, so the “storm track” or preferred pathway for storms is largely determined by the jet stream’s location throughout the cool season.

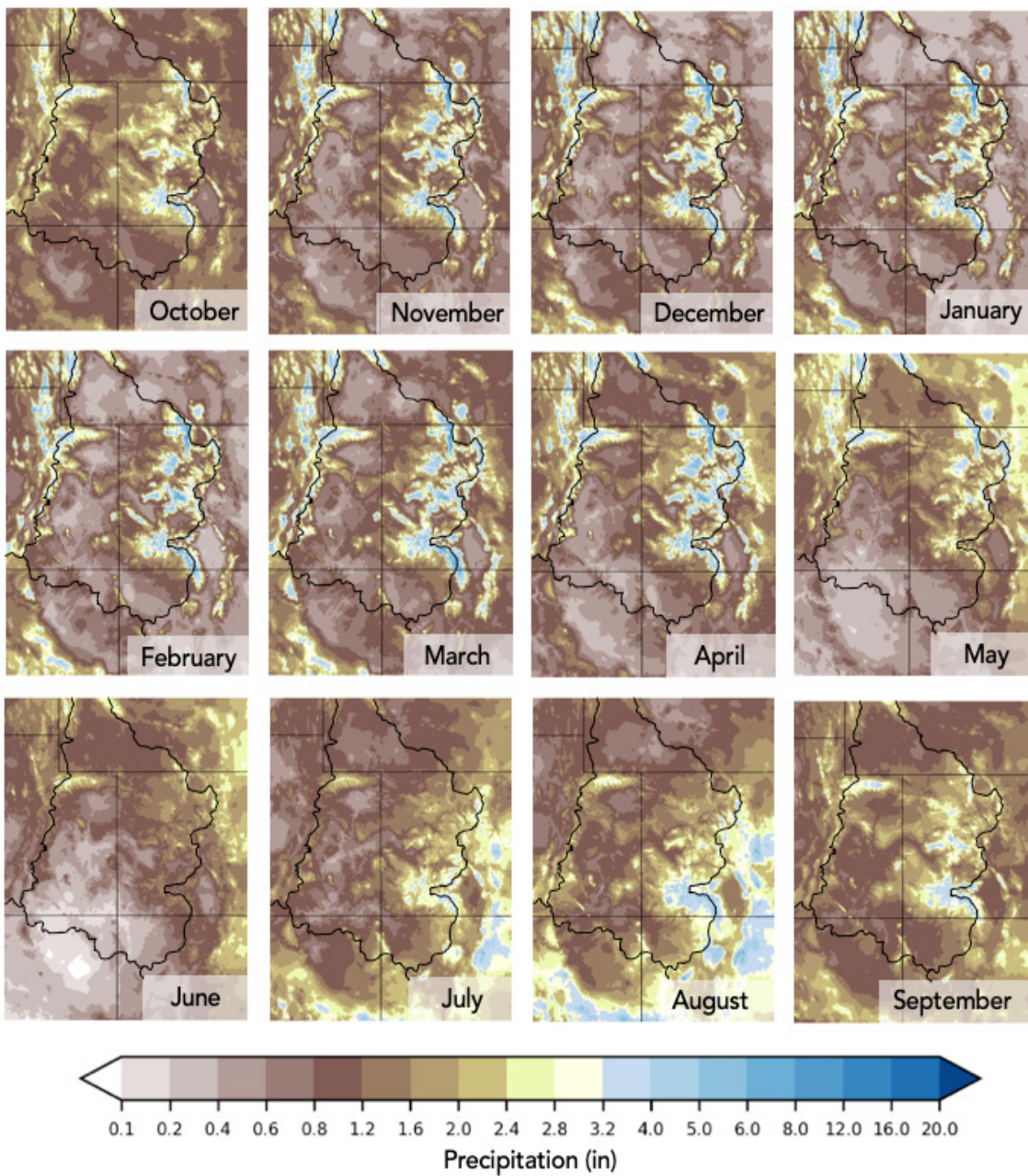


Figure 2.2

Average monthly precipitation (1981–2010) for the Upper Basin and headwaters of the Lower Basin. See text for description of the seasonally varying processes that contribute to these patterns. (Source: PRISM 800-m gridded data <http://prism.oregonstate.edu>; maps were generated by the Western Regional Climate Center https://wrcc.dri.edu/Climate/prism_precip_maps.php).

The position and activity of the storm track from October through May is the critical climatic driver of annual precipitation in the basin's headwaters, and thus of annual runoff. A single winter storm may bring 5–10% of annual precipitation to portions of the Upper Basin headwaters, so the occurrence of a handful of strong storms can make the difference between a drought year and a normal runoff year for the basin, or between a normal year and a wet year (Bolinger, Kummerow, and Doesken 2014). While individual storms move across the basin in 1–2 days, the storm track that they follow may persist in one location for several days to a few weeks.

In midwinter (December–February), as the north-south temperature gradients reach their maximum, the mid-latitude storm track can split, and storms that follow the southern track will impact Lower Basin headwaters such as the Mogollon Plateau. These storms are less frequent than those affecting the Upper Basin but usually carry more moisture, drawing from more southerly and thus warmer Pacific moisture sources. Some of the storms reaching the West Coast along either pathway may entrain very long and concentrated plumes of low-level (<5,000') moisture, known as atmospheric rivers, or AR, originating in the tropical Pacific. AR events have been recognized as the primary mechanism of extreme wintertime precipitation and flooding along the West Coast (Cayan et al. 2016). While the moisture transport in AR events is much reduced by interaction with the Coast Range and Sierra Nevada in California as the storm supporting the AR moves inland, of the 30–60 AR events that reach the West Coast annually, roughly 5–10 events bring substantial precipitation to at least some of the Lower Basin, and 3–6 to the Upper Basin (Ralph et al. 2019).

In April and May, storms affecting the Upper Basin become less frequent as the westerly winds begin to weaken and shift northward, but tend to carry more moisture per storm because of the warmer springtime temperatures. In the Lower Basin, the southern storm track can still be active but the individual storms dry out (Lareau and Horel 2012), initiating a spring dry period of 2–3 months between winter and summer peaks in precipitation. Throughout the entire basin, especially in the Lower Basin, June is a relatively dry month, with infrequent large-scale storm systems and scattered convective storms (i.e., thunderstorms).

In mid to late summer (July–September), intense heating of the land surface of northern Mexico and the Southwest induces a shift in the prevailing winds to southerly, drawing moist subtropical air northward. This pattern is known as the North American Monsoon or NAM (Adams and Comrie 1997; Sheppard et al. 2002). The often-daily convective storms associated with the NAM primarily affect the Lower Basin, with nearly all locations in Arizona and western New Mexico receiving 35–50% of the annual precipitation during the July–September period (Sheppard et al. 2002). As the intrusion of the NAM moisture plume advances northward in late

summer, the southern half of the Upper Basin sees increasing convective activity and precipitation as well (Jana et al. 2018). During the late summer and fall, landfalling Pacific tropical cyclones bring additional substantial moisture to the Lower Basin in some years (Hereford and Webb 1992). The net effect of these typical seasonal spatial patterns (Figure 2.2) is that different parts of the basin have characteristic precipitation seasonality, reflecting both north-south and elevational gradients (Sheppard et al. 2002; Lukas et al. 2014).

The high-elevation headwaters of the Upper Basin have consistently high monthly precipitation from November through April, with generally lower precipitation in the other months. The low and mid-elevations of the Upper Basin have a more even distribution, with a May peak from northern Colorado northward, and a fall peak to the south. Locations in the Lower Basin at all elevations have a pronounced peak in July–September associated with the NAM, and a secondary peak in December–March.

2.4 Influence of topography and elevation

As described above, there are general differences between Upper Basin and Lower Basin precipitation and its seasonality that reflect latitudinal (north-south) differences in key atmospheric dynamics. But the land itself—topography and elevation—is even more important in driving the sharp local and regional gradients in precipitation and temperature, with profound implications for water supply.

The key mechanism is *orographic lift*: Moist air masses are forced upslope by the terrain, cooling as they rise above the condensation level, where precipitation can occur (Barry and Chorley 2010). For a given parcel of moist air, the more rapid the vertical uplift, the greater the precipitation rate. Most mountain ranges in the Upper Basin are oriented north-south, creating abrupt barriers to the prevailing westerly moisture flow and enhancing orographic lift. Precipitation rates in a given storm event generally increase with increasing elevation on the windward (usually west-facing) mountainside. This is mirrored on the leeward (usually east-facing) side of the range; the upper elevations of the leeward side generally receive ‘spillover’ precipitation, but further downslope the air mass becomes progressively drier during its descent, creating a rain shadow effect. These orographic effects on precipitation are most pronounced in the winter when winds are the strongest (Redmond 2003). In the summer, although winds are weaker and tend to be more southerly or easterly, upslope forcing of moist air masses still occurs and can initiate convective storms over high terrain, such as the Mogollon Rim in Arizona.

The aggregate of these orographic effects accounts for nearly all of the local-scale variability in annual and monthly precipitation shown in Figures

orographic lift

A process in which air is forced to rise and subsequently cool due to physical barriers such as hills or mountains. This mechanism leads to increased condensation and precipitation in higher terrain.

2.1 and 2.2. Typically, range and plateau crests receive 2–5 times more precipitation than the adjacent basins or valley bottoms (Redmond 2003). The familiar gradient in temperature with increasing elevation also has a predictable physical basis; temperatures cool by about 3.5°F per 1000' of elevation gain due to falling atmospheric pressures with elevation (Sospedra-Alfonso, Melton, and Merryfield 2015). In winter, this relationship weakens at lower elevations due to the propensity for denser cold air to pool in basins and valley bottoms, leading to localized temperature inversions, especially when snow is on the ground. But on an annual basis, the observed gradient in temperature mirrors the gradient in precipitation in that both very closely reflect the topography (Figure 2.1). Gridded climate data products (see Chapter 4) must emulate these gradients in order to realistically interpolate temperature and precipitation values between weather stations.

From the standpoint of water balance and runoff, the elevation-related precipitation and temperature gradients operate in the same direction: compared to lower elevations, higher elevations see both greater moisture inputs (i.e., precipitation) *and* lower ET losses, due to cooler temperatures and increased cloudiness reducing incoming solar radiation. Also, at higher elevations, a greater fraction of precipitation falls as snow, which is less susceptible to atmospheric re-uptake than rain. As an example, elevations near treeline (about 11,500') in western Colorado typically receive about 40" of precipitation annually, mostly as snow, and hydrologic modeling (Chapter 6) suggests that roughly 50% (20") of that is lost to ET, leaving 20" of runoff (Figure 2.1). A nearby mid-elevation site at 8000' may receive about 20" of precipitation annually, about half as snow, but roughly 80% of the precipitation (16") is lost to ET, leaving 4" of runoff—80% less runoff than the high-elevation case.

2.5 The basin's snowmelt-dominated hydrology

As indicated in the previous discussion, a disproportionate share of basin-wide precipitation falls in the high-elevation headwaters, where it also falls primarily as snow (Figure 2.3). These cooler mountain areas see lower fractional ET losses in all seasons, and precipitation falling as snow is less prone to ET losses than rain, particularly when falling on a snowpack surface and insulated from ground warmth. Accordingly, like most other basins in the western U.S., the primary component of runoff in the Colorado River Basin is snowmelt. Multiple studies have estimated the contribution of snowmelt to annual streamflow for portions, or all, of the mountainous West ranging from 60% to 85%, as compiled in Li et al. (2017). The most recent West-wide modeling analysis estimated that the contribution of snowmelt to total Upper Basin runoff is 71%, with a higher fraction (>80%) in the high-elevation headwaters sub-basins (Li et al. 2017).

For comparison, just about 50% of the total Upper Basin precipitation falls as snow (Rumsey et al. 2015); thus, the snow fraction of basin-wide annual precipitation has over twice the runoff efficiency of the rain fraction.

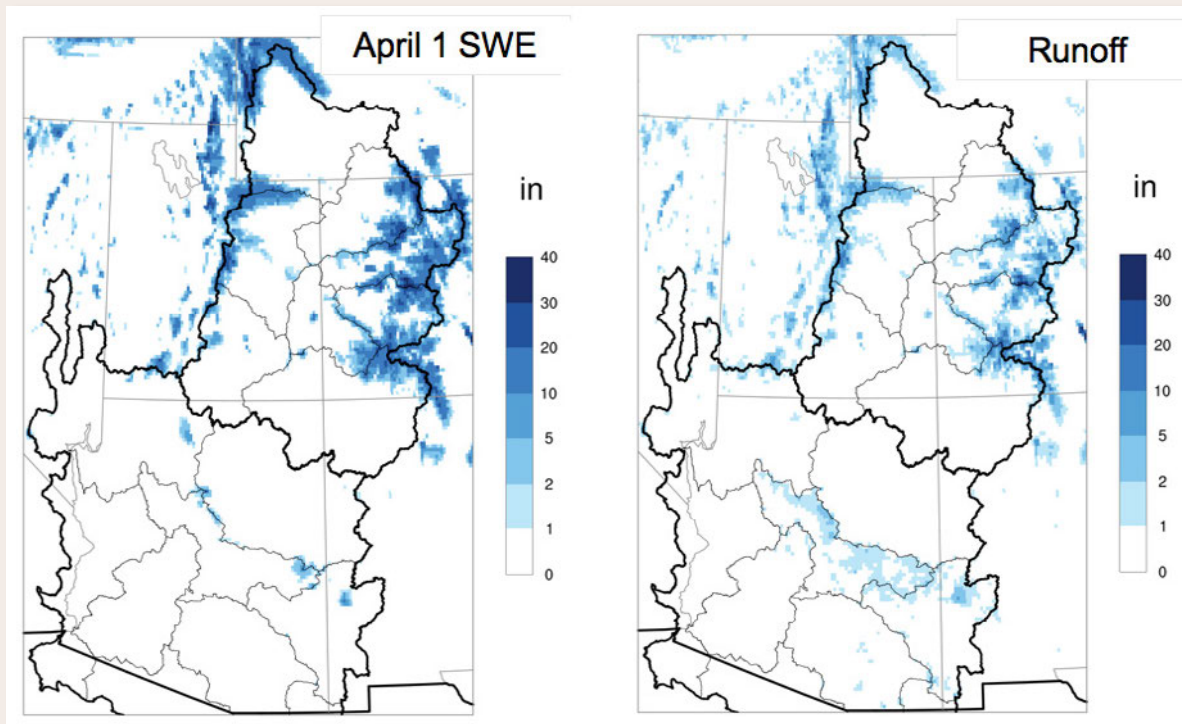


Figure 2.3

Colorado River Basin modeled average April 1 snow water equivalent (SWE; left), and modeled average annual runoff (right). Note that the areas producing $>1''$ of runoff in the Upper Basin closely coincide with the areas in which a seasonal snowpack builds. In the Lower Basin, much of the snowpack has already melted out by April 1; the snowpack is more extensive on March 1. (Data: Livneh et al. 2013)

The peak value of seasonal snow water equivalent (SWE), which usually occurs within 3–4 weeks of April 1 for most of the Upper Basin’s headwaters (see Figure 2.4), is an excellent predictor of April–July runoff and thus is closely monitored (Chapter 5) for runoff forecasting and water-supply planning (Chapter 8). The snowpack of the basin is effectively an enormous seasonal reservoir that fills and empties every year. This reservoir has average seasonal peak volume of 17–18 maf in the Upper Basin, equivalent to 70% of the capacity of Lake Powell, according to spatial SWE estimates (Schneider and Molotch 2016; see Chapter 5).

The basin’s snowpack accumulates over a 4- to 7-month period, with accumulation typically beginning in October at higher elevations in the Upper Basin, and beginning increasingly later in the fall or winter as one

moves downslope and southward in the basin. The winter climate (November–March) in the Upper Basin is colder than in the other mountain regions of the western U.S. (Lute, Abatzoglou, and Hegewisch 2015) and so the snowpack is less prone to melt loss prior to the spring peak. The peak SWE value in wind-sheltered locations at high elevations (e.g., SNOTEL sites, Chapter 5) typically averages 15”–50” in the Upper Basin, and 3”–10” in the Lower Basin (Figures 2.3 and 2.4).

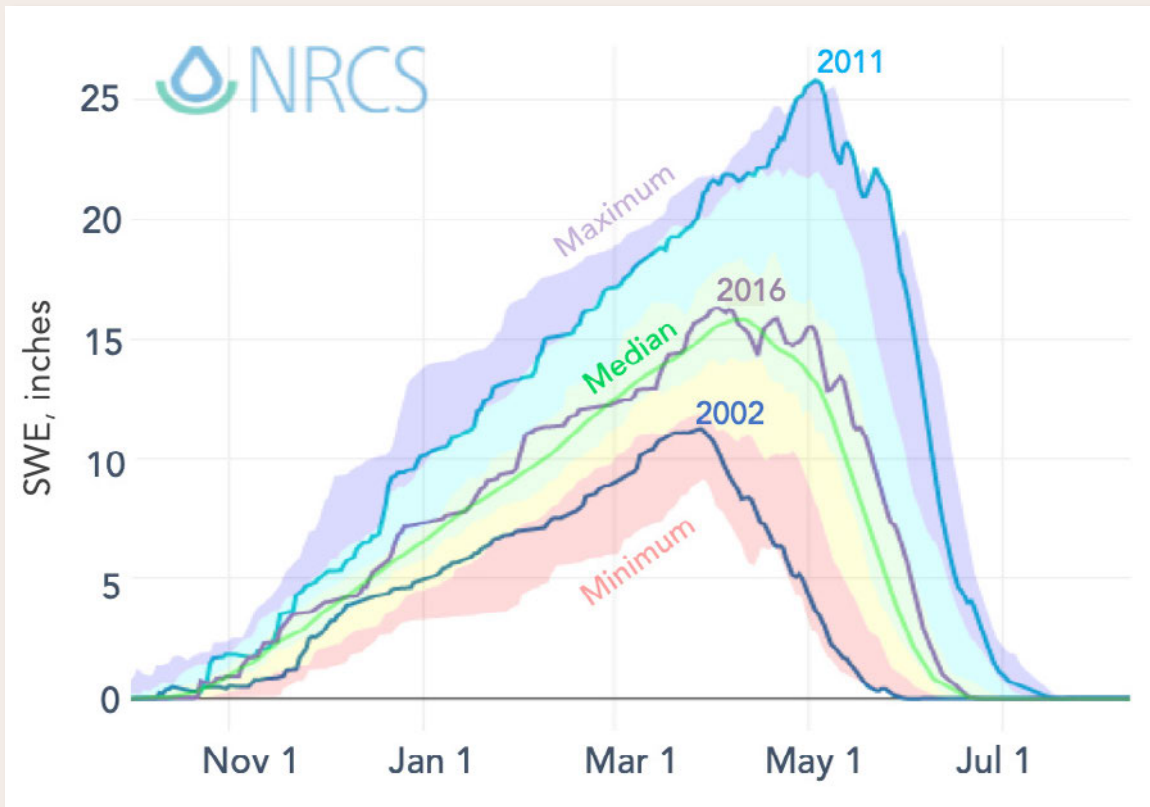


Figure 2.4

Historical snowpack accumulation and melt curves for the Colorado River headwaters above Cameo (average of ~30 SNOTEL sites), shown in inches of snow water equivalent (SWE). The colored shaded bands are bounded by the following percentiles (1981–2010): 1st (minimum), 10th, 30th, 70th, 90th, and 100th (maximum). Selected years are shown to illustrate a much-above-normal snowpack (2011), a near-normal snowpack (2016), and a much-below-normal snowpack (2002). Note that larger snowpacks tend to peak later, and that smaller snowpacks have slower daily melt rates, i.e., the declining limb is not as steep. (Source: adapted from NRCS Colorado Snow Survey)

Field studies and modeling suggest that the equivalent of 10–20% of peak SWE over the basin is lost to sublimation—the transition of water from solid phase directly to gaseous phase—during the course of the season (Hood, Williams, and Cline 1999; Phillips 2013; Hultstrand and Fassnacht 2018). The highest losses occur during the spring months (March–May) when air

temperatures and shortwave (solar) radiation are higher. The meltout of the snowpack occurs over 1-2 months, much faster than accumulation.

Snowmelt typically begins in earnest in February or March in the Lower Basin, and in April or May in the Upper Basin. Snowmelt is driven primarily by greater shortwave radiation due to higher sun angles and longer days, though warmer air temperatures, especially above-freezing air temperatures at night, prime the snowpack for faster melt.

The snowmelt rate is enhanced when the snow surface is dusty; typically, 3–10 dust-on-snow events affect parts of the Upper Basin each spring, particularly the San Juan Basin, with the aggregate dust loading and thus impact on melt rates varying substantially from year to year (Deems et al. 2013; Clow, Williams, and Schuster 2016; Painter et al. 2018). See the sidebar in Chapter 5 for further description of the dust-on-snow phenomenon and its effect on basin hydrology.

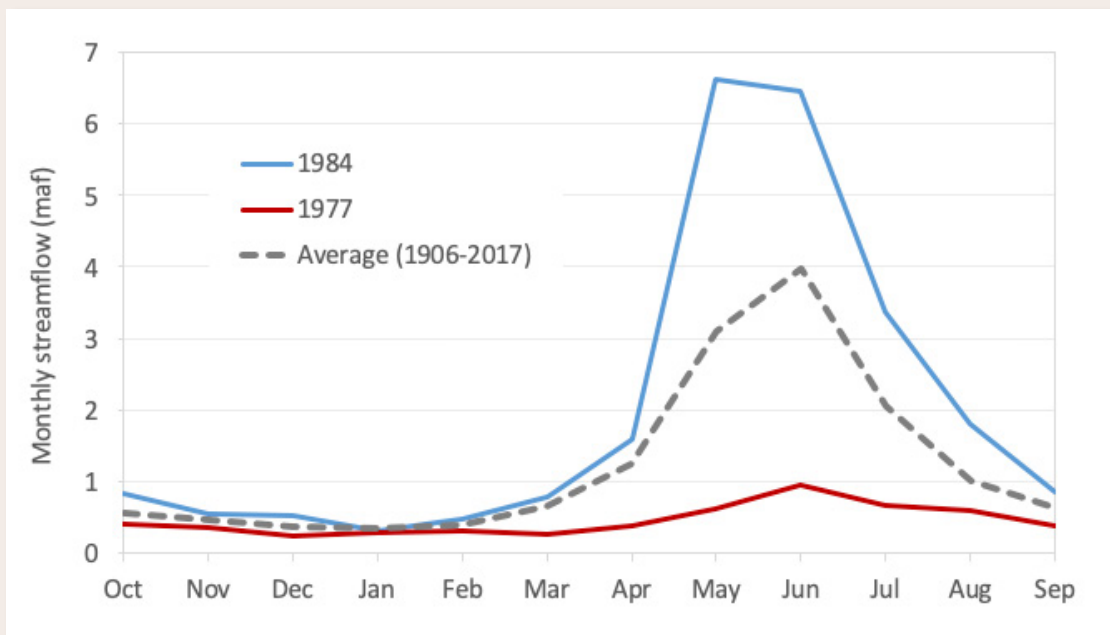


Figure 2.5

Average annual hydrograph (monthly natural flows) for the Colorado River at Lees Ferry for the 1906–2017 period, compared with the annual hydrographs for the lowest-flow year (1977) and the highest-flow year (1984) on record. All three traces show low flows in winter and early spring, the rise to a May/June peak, and declining limb in summer and early fall. (Data: Reclamation, after Prairie and Callejo 2005)

The dominance of snowmelt in driving annual runoff is clearly expressed in the shape of the annual hydrograph for all streams and rivers in the Upper Basin, and for many streams and rivers in the Lower Basin as well. Figure 2.5 shows the long-term average hydrograph for natural flows at Lees

Ferry, with the characteristic rapid rise in spring with snowmelt, a peak typically in May or June, and an equally steep declining limb back to baseflows by late summer. About 70% of the annual flow, on average, occurs during the April–July period typically used for seasonal water supply forecasting, while over 80% of the annual flow occurs during a longer period (March–August) that is more inclusive of snowmelt processes.

While snowmelt contributes the large majority of total runoff in the basin, cool-season (October–April) rainfall at lower elevations can make substantial contributions to runoff in some years, particularly in the Lower Basin. Warm-season (May–September) rain generally makes very little contribution to the basin runoff, because ET rates are much higher during those months, especially during June, July, and August (Julander and Clayton 2018). However, rain during the growing season does play an important role in moderating water demand for agriculture and urban outdoor use.

2.6 Groundwater and surface water

In the Colorado River Basin, as elsewhere, groundwater resources are not quantified or understood nearly as well as surface water resources (Rumsey et al. 2015)—and are not well integrated into basinwide modeling, management, and planning. Groundwater is difficult to observe and manifests in extremely diverse forms, frustrating clear conceptualization and effective management. On one end of the spectrum, a groundwater body (i.e., aquifer) may have very high connectivity with surface waters (streams, rivers, lakes), a residence time of the water measured in weeks or months, and high temporal variability; on the other end, an aquifer may have little connectivity with surface waters, a residence time of thousands of years, and little variability over time apart from withdrawals for human use (Maxwell et al. 2016). In the latter case, the stored water represents recharge accumulated over millennia, including under different climate regimes than at present. Both of these extremes are present in the Colorado River Basin and other basins around the West.

Given the scope of this report, a central question regarding groundwater in the basin is its role in the availability, variability, and predictability of surface water. Using geochemical tracers in stream water that provide evidence of subsurface contact, Miller et al. (2016) estimated that on average about 50% of the (surface) streamflow of the Upper Basin derives from groundwater. In just the high-elevation catchments producing most of the Upper Basin’s runoff, the groundwater fraction of streamflow is lower, around 30% (Miller et al. 2016; Carroll et al. 2018).

These may seem like unexpectedly high fractions for a basin with a snowmelt-dominated hydrologic regime, in which the annual streamflow

volume is very strongly correlated with that year's snowpack volume. Groundwater contributions to streamflow in mountain catchments were long believed to be minimal because of low aquifer storage potential and steep hydraulic gradients (Carroll et al. 2018). The resolution of this apparent conundrum is that only a portion of each spring's snowmelt runs off on the surface directly to streams and rivers that same season; instead, much of the snowmelt enters the subsurface and becomes new groundwater. Stored groundwater in high-elevation catchments is displaced by this new snowmelt recharge and discharged to the stream channel as groundwater (Williams et al. 2015). In other words, the new snowmelt volume enters aquifers that have relatively high connectivity, and pushes out a proportional volume of older groundwater to streams.

Miller et al. (2016) also show, as would be expected, that the high-elevation catchments have the highest groundwater discharge to surface water per unit area. In these catchments, the surface drainage network is denser than at lower elevations, and thus subsurface flow paths are generally shorter and shallower, with shorter residence times, mainly on the order of months to several years (Williams et al. 2015; Maxwell et al. 2016). In the lower-elevation catchments of the Upper Basin, which collectively contribute much less to overall basin streamflow, the percentage of surface flow deriving from groundwater is greater, reflecting longer and deeper subsurface flow paths of groundwater to streams, with longer residence times (Miller et al. 2016; Maxwell et al. 2016).

These findings collectively indicate that groundwater is tightly coupled to surface water in the most hydrologically productive catchments in the basin. It also appears that groundwater residence does not significantly modify the climate-driven signal of interannual variability as manifested in snowmelt-runoff volumes. Rosenberg et al. (2013) found that hydrologic model simulations of historical streamflows in the Upper Basin yielded similar skill regardless of whether a representation of groundwater was included in the model. They concluded that the absence of explicit groundwater information in the seasonal streamflow forecast models currently used by the Colorado Basin River Forecast Center (CBRFC) and Natural Resource Conservation Service (NRCS) was probably not detrimental to those forecasts, at least in the Upper Basin (Chapter 8). The CBRFC does model the initial (fall) soil moisture state in their streamflow forecast model (Chapter 5), which may capture variations in shallow groundwater storage as well. Groundwater is closely tied to soil moisture, since most groundwater comes from the fraction of soil moisture that escapes evapotranspiration and percolates down through the unsaturated vadose zone to the water table, recharging the fully saturated groundwater aquifer (Shelton et al. 2009).

2.7 Hydroclimatic variability of the basin

Interannual variability

A critical feature of the natural river system has been the large variability in hydroclimate conditions. Looking first at interannual variability (Figure 2.6), annual precipitation in the Upper Basin has varied by over a factor of 2.1 from the driest water year in the historical record (1977; 11.4”) to the wettest water year (1997; 24.4”). Because the fraction of precipitation lost to ET is large (on average, 80% across the Upper Basin) and this fraction is greater in dry years and lower in wet years, the natural streamflow of the Upper Basin is even more variable than precipitation, varying by a factor of about 4.5 from the lowest-flow water year (1977; 5.4 maf) to the highest-flow water year (1984; 24.4 maf).

This difference in the respective extremes of variability implies that the precipitation sensitivity (or elasticity) of streamflow is roughly 2, since a 2-fold change in precipitation is associated with about a 4-fold change in streamflow (Figure 2.6). More explicit assessments using empirical analyses or hydrologic models across the full range of variability suggest that the precipitation sensitivity of streamflow in the Upper Basin is likely between 2.0 and 3.0; i.e., a 10% change in precipitation is associated with a 20-30% change in streamflow (Vano, Das, and Lettenmaier 2012; Hoerling et al. 2019).

The very close similarity between the variability in Upper Basin precipitation and Upper Basin (Lees Ferry) natural streamflow is apparent in Figure 2.6. Statistically, the precipitation record explains 61% of the variance in streamflow over the full period of overlap (1906–2019), and an even higher proportion (74%) over the 1980–2019 period. It is not clear if this apparent increase in the strength of the relationship between precipitation and streamflow in recent decades is a function of increasing robustness of the data underlying the basin-wide precipitation record (see Chapter 4) and the natural streamflow record, or actual changes in the physical relationship.

Temperature does covary with precipitation during the warm season (i.e., dry April–September periods tend to also be warmer than normal, and wet April–September periods tend to also be cooler than normal). Also, temperature has an independent influence on streamflow, as will be detailed later in this chapter. Even so, precipitation is the most important driver of interannual streamflow variability in the basin, by a wide margin (Nowak et al. 2012; Woodhouse et al. 2016; McCabe et al. 2017), which makes it challenging to accurately assess the role of other factors, such as temperature or antecedent (previous fall) soil moisture.

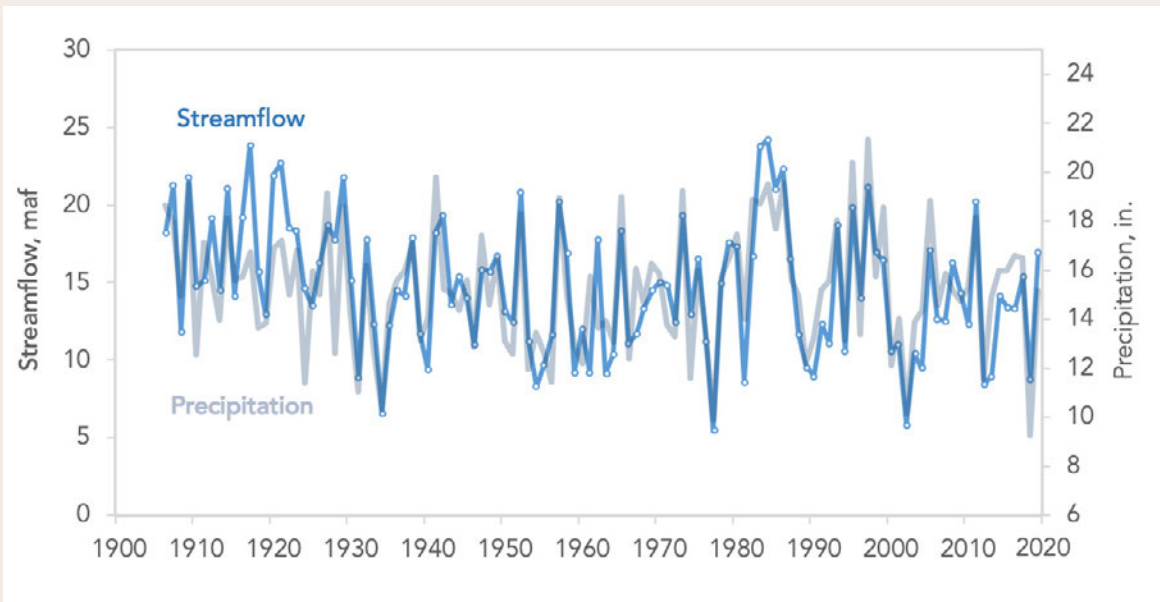


Figure 2.6

Upper Basin water-year precipitation compared with Colorado River at Lees Ferry water-year natural streamflow, 1906–2019. The correlation between the two time-series is 0.77 ($R^2 = 0.61$) over the entire record, with higher correlations over more recent periods. (Data: precipitation, NOAA NCEI; streamflow, Reclamation)

A common measure of the magnitude of interannual variability in a time-series is the coefficient of variation (CV), which is the ratio of the standard deviation to the mean. A higher CV indicates greater variability. The CV of annual precipitation is 0.16 in the Upper Basin, and slightly higher in the Lower Basin (Table 2.2). As noted above, the variability of annual streamflow is higher than that of precipitation; the CV of Upper Basin (Lees Ferry) annual natural streamflow (1906–2016) is 0.29. This is greater than for annual streamflow of the Columbia River (CV: 0.18; Vano, Das, and Lettenmaier 2012) but similar to the median CV (0.31) of the annual streamflow of 1,221 rivers in a global database (McMahon et al. 2007). Variability in annual streamflow is much higher in the Lower Basin compared to the Upper Basin, because the warmer climate and greater fractional ET losses further accentuate the variability in precipitation. For example, Little Colorado River annual gaged streamflow has a CV of 0.73 (1906–2016), comparable to the CV for the relatively unimpaired headwaters of the Salt River, which share a watershed divide with the Little Colorado. The interannual variability in streamflow itself varies in magnitude over time (Pagano and Garen 2005).

Table 2.2

Variability and persistence in basin precipitation and streamflow over the 1906–2016 period. See text for explanation of indices. (Data: runoff from Reclamation, after Prairie and Callejo (2005); precipitation from NOAA NCEI)

Region/gage and variable	Coefficient of Variation (CV)	Lag-1 Persistence
Upper Basin annual precipitation	0.16	-0.10
Lees Ferry annual natural streamflow	0.29	0.23
Lower Basin annual precipitation	0.21	-0.01
Little Colorado annual gaged streamflow	0.73	0.05

Another important dimension of variability is persistence: the degree to which one year's value is similar to the previous year's value. Greater persistence indicates a tendency toward longer runs of wet years and dry years, with implications for storage needs and reservoir management. In both the Upper and Lower Basins, this year-on-year persistence (lag-1 autocorrelation) of Upper Basin annual precipitation over the 1906–2016 period is not statistically significant (Table 2.2); in other words, there is no meaningful relationship between current-year precipitation and the next year's precipitation.

Persistence in streamflow is often greater than that for precipitation, since soil moisture and groundwater storage anomalies generally produce a carry-over effect after wet years, as well as after dry years. Upper Basin (Lees Ferry) annual natural streamflow does have significant persistence over the 1906–2016 period, with a lag-1 autocorrelation of 0.23. Lower Basin gaged annual streamflows show less short-term persistence, with lag-1 autocorrelations ranging from 0.05 to 0.10 over the 1906–2016 period for the Little Colorado, Bill Williams, and Virgin Rivers.

Decadal-scale and longer variability

While the large storage capacity of Colorado River Basin reservoirs buffers the system from many impacts of extreme annual variability (e.g., the record low flow year of 1977), departures from average conditions over several years and longer can accumulate into deficits of 20 to 40 maf that heavily deplete system storage, as with the most recent period. Thus, it is important to consider decadal-scale variability in basin precipitation and streamflow, which can be very simply depicted by a 10-year running average on the annual values, as in Figure 2.7 for Upper Basin streamflow.

Over the observed Lees Ferry record, the 10-year running average has varied by about +/-20% of the long-term average streamflow, with peaks above 18 maf in the 1920s and 1980s, and low points of 12.0–12.5 maf in the 1960s and 2000s. The longest excursions away from the long-term average have been on the order of 20–30 years, and occurred roughly around 1906–1930 (above), 1955–1980 (below), and 2000–2019 (below). With so few of these excursions to examine, it is difficult to say from the observed record alone if the 25-year period of 17–18 maf at the beginning of the record is unusual behavior for the system; however, as described below, tree-ring data suggests that it is unusual.

Another way of examining decadal-scale variability is to use a weighted smoothing filter that emphasizes the values occurring in the middle of the smoothing period. This will make apparent any cyclical behavior that has a wavelength similar to the smoothing period. Figure 2.7 shows a 9-year weighted filter applied to the Lees Ferry streamflow record. While the filtered record stays close to the running average for most of the record, after 1980 the filtered record departs from the running average and shows stronger peaks and troughs up through the late 2000s. This quasi-decadal oscillation after 1980 was also seen in a wavelet analysis performed by Nowak et al. (2012). They found this oscillation to be the strongest periodic variability at any wavelength in the observed Lees Ferry streamflow record—but it was only active over the most recent three decades of the record.

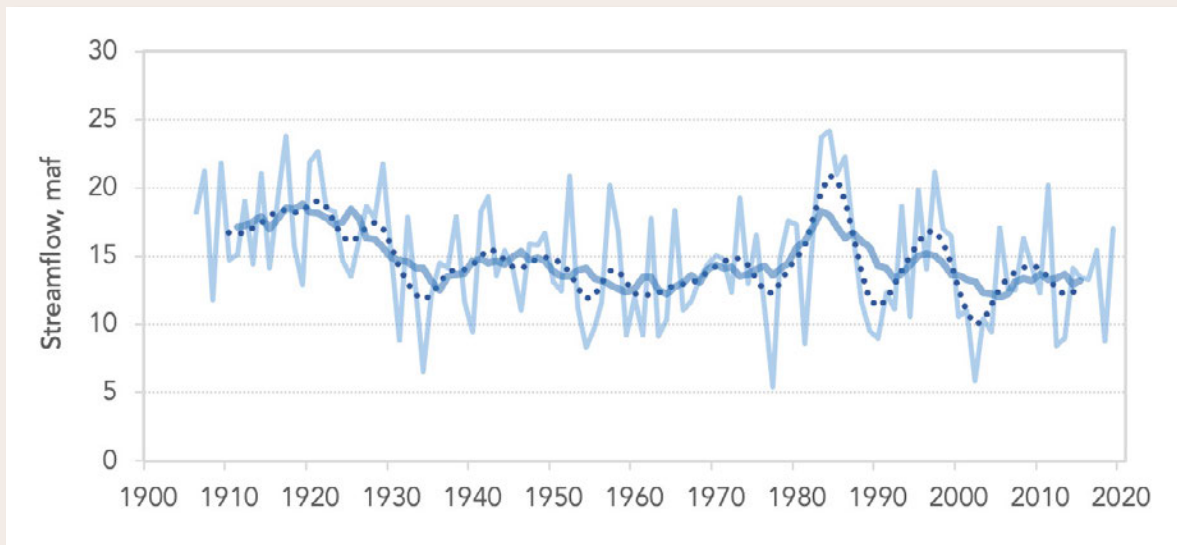


Figure 2.7

Colorado River at Lees Ferry water-year natural streamflow (light blue), with a 10-year running average plotted on the 6th year (dark blue), and a 9-year Gaussian weighted filter (dotted), 1906–2019. (Data: Reclamation)

A much longer perspective on decadal-scale variability in the Upper Basin can be seen in the 10-year running mean of a tree-ring reconstruction of Lees Ferry natural streamflow that spans from the years 762 to 2005 (Figure 2.8; Meko et al. 2007). With this much longer context—about 10 times longer than the observed record—the extended high-flow period from 1906–1930 appears to be quite unusual, with only two prior periods (late 1100s and early 1600s) that appear to be comparable. On the opposite extreme, there appear to be many extended low-flow periods with greater cumulative deficits than the 1955–1980 period, or the current 2000–2018 period. Most notable among these are the low-flow periods of roughly 1865–1905 and 1130–1160. Nowak et al. (2012) also performed a wavelet analysis on a shorter tree-ring reconstruction of Lees Ferry flows (back to 1490) and found that a quasi-decadal oscillation was present only intermittently, for no more than 30–40 years at a time, most prominently in the early 1500s, early 1700s, and mid-1800s.

Multi-decadal oscillations (about 20–80 years) were present during most of the 500-year record, but with different characteristic wavelengths. The 30-year running mean of the Meko et al. (2007) Lees Ferry reconstruction (Figure 2.9) shows that oscillations with a wavelength close to 30 years were prominent around 1200, around 1600, and over the historical period from the late 1800s to present. It also indicates that the 30-year average—a period often used in climatology to describe the average climate—is itself subject to substantial variability.

The key message of the reconstructed tree-ring record is that the variability of Colorado River hydroclimate is greater than one would infer from the observed record alone. A diverse array of decadal, multi-decadal, and century-scale flow sequences are present in the tree-ring record. As detailed in Chapter 10, the safest assumption is that any of these sequences could recur in the future due to natural variability alone.

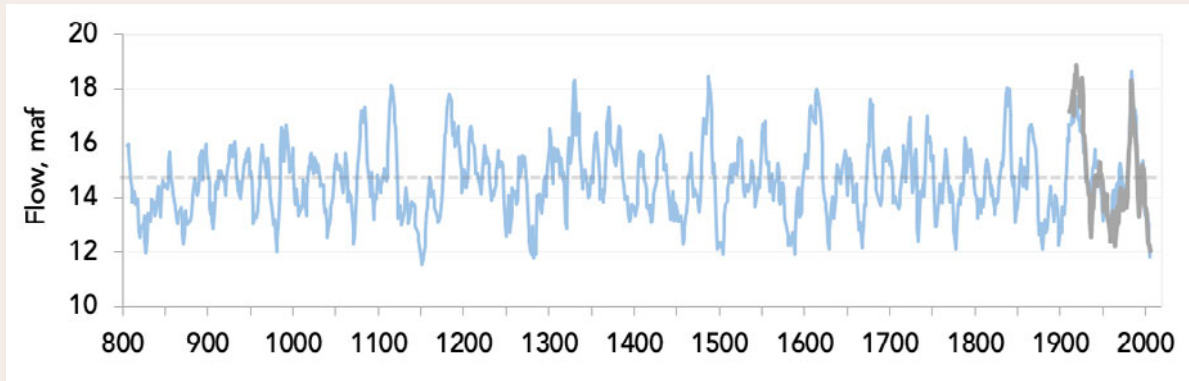


Figure 2.8

The 10-year running average of reconstructed Colorado River at Lees Ferry natural flow 762–2005 (blue) and the 10-year running average of observed natural flow 1906–2005 (gray). The long-term reconstructed mean of 14.7 maf is shown by the dashed line. (Data: Meko et al. 2007; treeflow.info)

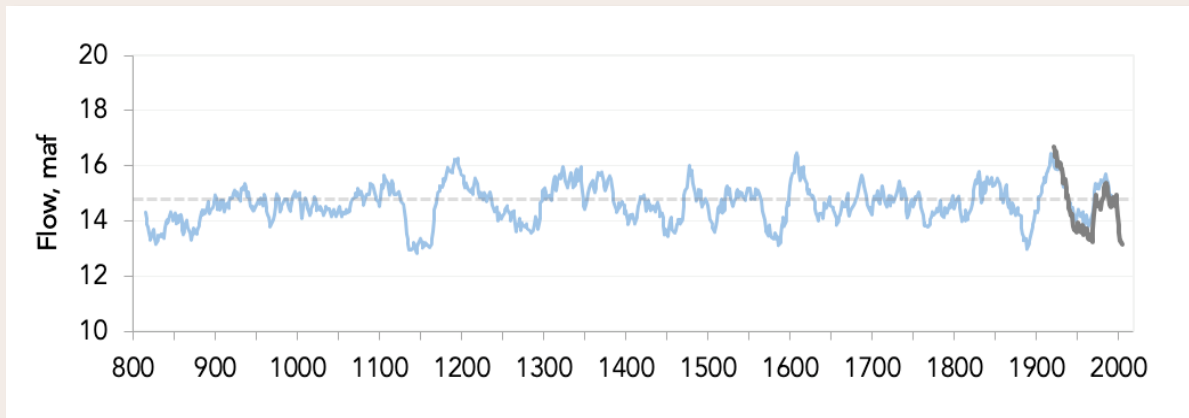


Figure 2.9

The 30-year running average of reconstructed Colorado River at Lees Ferry naturalized flow 762–2005 (blue) and the 30-year running average of observed flow (gray). The long-term reconstructed mean of 14.7 maf is shown by the dashed line. (Data: Meko et al. 2007; treeflow.info)

2.8 Mechanisms of hydroclimate variability and their predictive value

In general, the climate variability described in the previous section is the net effect of chaotic fluid motions in the Earth’s atmosphere and oceans as they act to maintain global equilibrium in energy and moisture, or what is called “internal variability.” The enormous heat storage capacity and slower movement of the oceans leads to patterns or modes of climate variability that play out over months to years, producing persistent and to some degree predictable influences on weather and climate over vast regions. This last point is especially important given the absence of consistent,

regular hydroclimatic cycles at interannual and longer time scales in the basin.

El Niño-Southern Oscillation (ENSO)

The El Niño-Southern Oscillation, or “ENSO,” is the most important pattern of interannual global climate variability, and much of the skill in seasonal climate forecasting around the world is derived from it. The vast tropical Pacific Ocean absorbs tremendous amounts of solar energy that is redistributed northward and southward toward the poles. The key features of ENSO are changes in the sea-surface temperatures (SSTs) of the eastern tropical Pacific Ocean, the atmospheric pressure difference between eastern Pacific high pressure and western Pacific low pressure (the Southern Oscillation), and changes in the location of persistent bands of tropical thunderstorms. The Oceanic Niño Index (ONI) shows the irregular 2- to 7-year time scale of the oscillation between the two phases of ENSO: the El Niño (warm phase) events and La Niña (cold phase) events (Figure 2.10).

teleconnection

A physical linkage between a change in atmospheric/oceanic circulation in one region (e.g., ENSO) and a shift in weather or climate in a distant region (e.g., the Colorado River Basin).

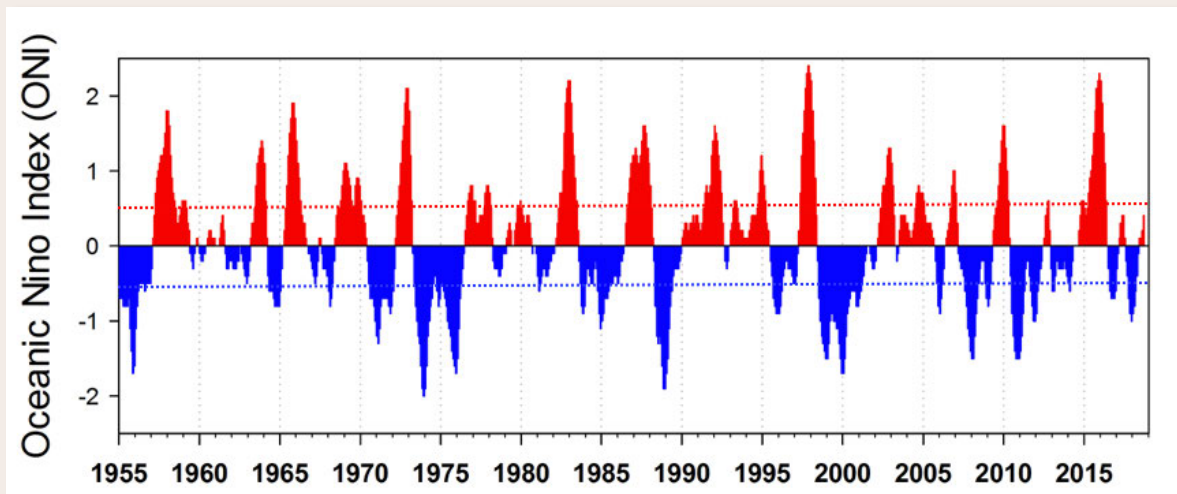


Figure 2.10

The monthly Oceanic Niño Index (ONI), 1955–October 2018. The ONI is a 3-month running average of sea-surface temperatures in the central tropical Pacific (Niño 3.4 region). Values greater than 0.5 (red dashed line) indicate El Niño conditions; values below -0.5 (blue dashed line) indicate La Niña conditions. (Source: NOAA [Northwest Fisheries Science Center](https://www.nwfsc.noaa.gov/research/divisions/fe/estuarine/oeip/cb-mei.cfm), <https://www.nwfsc.noaa.gov/research/divisions/fe/estuarine/oeip/cb-mei.cfm>)

Once an El Niño or La Niña event is established, often during summer, it tends to persist into the following calendar year. Thus, ENSO events impart some memory and seasonal predictability to the global climate system.

The massive transfers of energy accompanying ENSO influence the atmospheric circulation well beyond the tropics, including the position of

the jet stream and storm tracks over western North America (Figure 2.11). These “teleconnection” effects on the West were first described in the 1980s (Redmond and Koch 1991; Bradley et al. 1987). During El Niño events, the position of the cool-season storm track tends to shift southward, or split in two, such that the Southwest (i.e., the Lower Basin) receives higher than normal precipitation, while the Pacific Northwest is drier than normal. La Niña events see a strengthening of the normal winter pattern in which storm tracks are more northerly, and so the case is reversed: The Southwest tends to be drier than normal during La Niña, while the Pacific Northwest is wetter than normal (Cayan, Redmond, and Riddle 1999).

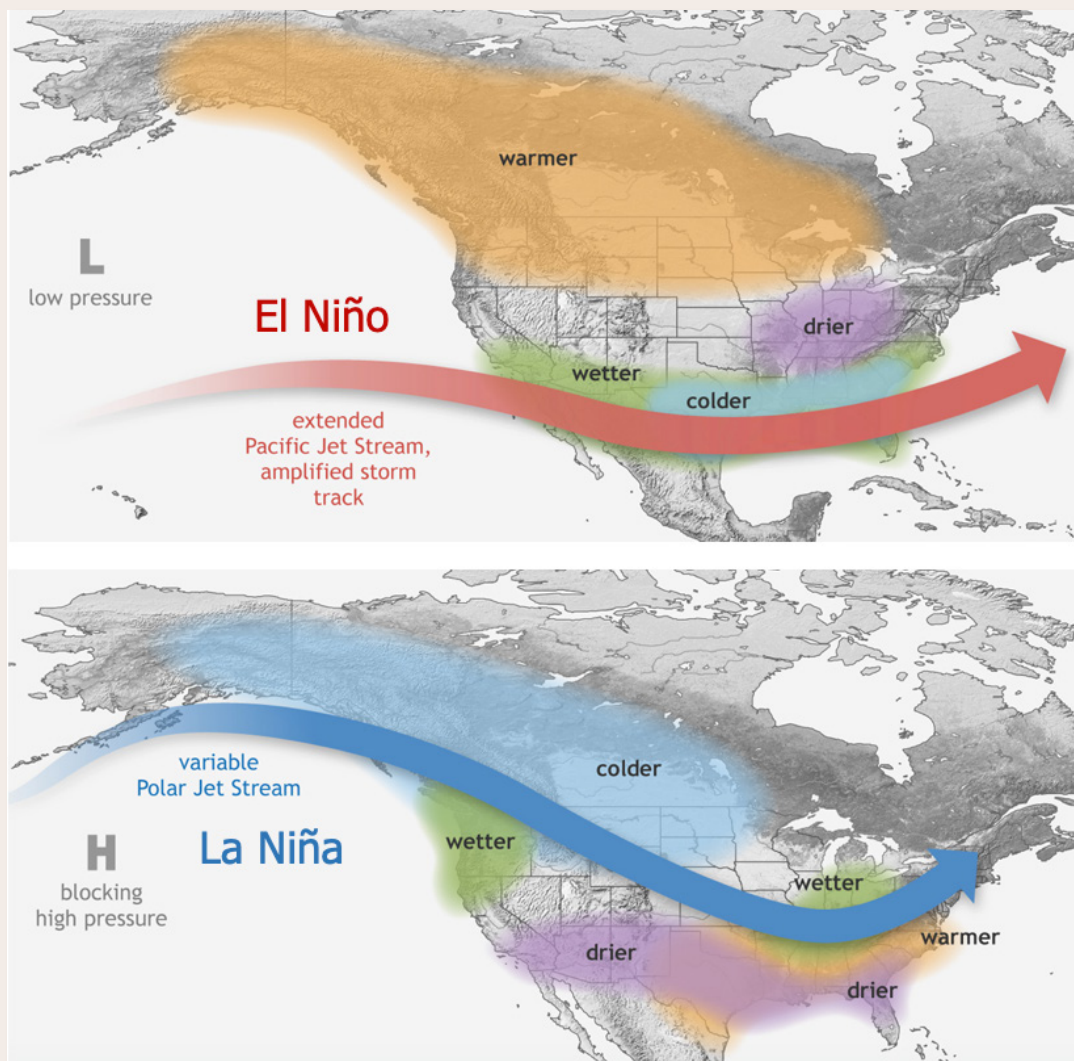


Figure 2.11

Typical changes in atmospheric circulation over North America associated with El Niño and La Niña events, and the corresponding regional climate anomalies that are likely to occur. (Source: adapted from NOAA, <https://www.climate.gov/news-features/featured-images/how-el-ni%C3%B1o-and-la-ni%C3%B1a-affect-winter-jet-stream-and-us-climate>)

In the past decade, a second “flavor” of El Niño event has been identified, with the maximum SST anomalies located in the Central Pacific (CP) in contrast with the Eastern Pacific (EP). In a CP El Niño, compared to traditional EP El Niño events, the winter drying influence on the Pacific Northwest is enhanced, but the winter wetting influence on the Southwest is similar (Yu and Zou 2013). It appears that CP El Niño events have become more common in recent decades (Freund et al. 2019).

For the Lower Basin, the ENSO influence on hydroclimate is strongest in the winter season, and ENSO state (observed or forecasted) is a better predictor of Lower Basin cool season (October–March) precipitation than of Upper Basin cool season precipitation (Figure 2.12). Note that while the correlations shown for the Lower Basin ($r = 0.4$ to 0.6) are statistically significant, they also indicate that most of the variability in cool-season precipitation is *not* statistically associated with ENSO. Also, the reliability of the ENSO signal in the Lower Basin is asymmetric: La Niña events are more likely to be dry than El Niño events are likely to be wet.

The Upper Basin lies across the transition region of the Southwest-Pacific Northwest ENSO dipole (Wise 2010), and so ENSO has less overall influence on Upper Basin cool-season precipitation and water-year streamflow than it does in the Lower Basin. Even so, there is some signal that can potentially be exploited for hydroclimate forecasting, especially in the northern and southern sub-basins of the Upper Basin (Figure 2.12).

The Upper Green River basin, and to a lesser extent the headwaters of the Yampa-White and Colorado rivers, tend to mirror the Pacific Northwest; i.e., wetter outcomes in La Niña. This mainly reflects a midwinter (December–February) tendency for the polar jet stream and storm track to be enhanced during La Niña, resulting in wetter conditions over the high elevations of southern Wyoming and northern Colorado, and conversely, more frequent blocking of westerly flow and storms in those areas during El Niño, resulting in drier conditions (Wolter, Dole, and Smith 1999). Further south in the Upper Basin, the San Juan River basin tends to mirror the Southwest and Lower Basin; i.e., wet in El Niño.

For Upper Basin-wide precipitation and streamflows (i.e., Lees Ferry), these opposing tendencies mostly cancel out, and it is hard to discern a clear tendency toward higher Lees Ferry flows in El Niño years and lower flows in La Niña years, even during strong events.

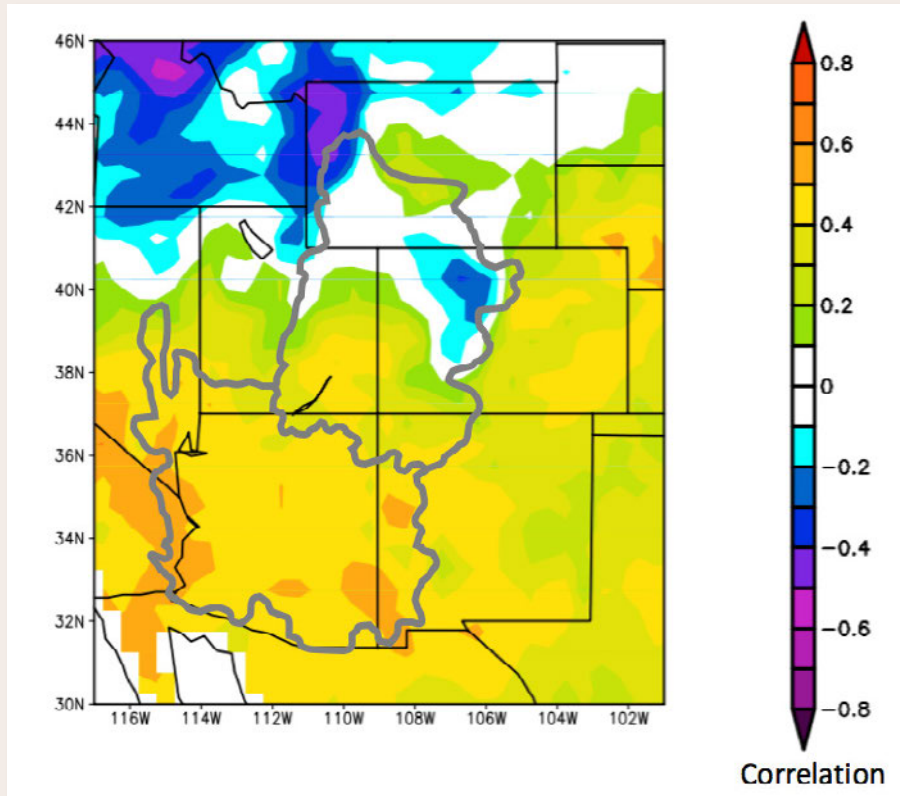


Figure 2.12

Correlation between October–March precipitation and August–January Niño 3.4 index from 1949–2014. Yellow and orange colors indicate areas that tend to be wetter during El Niño events and drier during La Niña events; blue and purple colors indicate areas that tend to be wetter during La Niña events and drier during El Niño events. (Source: NOAA ESRL Physical Sciences Division)

Figure 2.13 shows Lees Ferry water-year natural streamflows corresponding to El Niño ($n = 12$) and La Niña ($n = 12$) conditions in the beginning of the water year (i.e., fall) from 1980–2018. There are no meaningful differences in average or median flow between El Niño and La Niña cases, or between those and the ENSO-neutral cases ($n = 14$). The behavior at the lower tails of the distributions, however, appears more distinct: While there are no annual flows below 10 maf among the El Niño cases (0 of 12), 3 of 12 La Niña cases have flows below 10 maf, as do 4 of 14 ENSO-neutral cases.

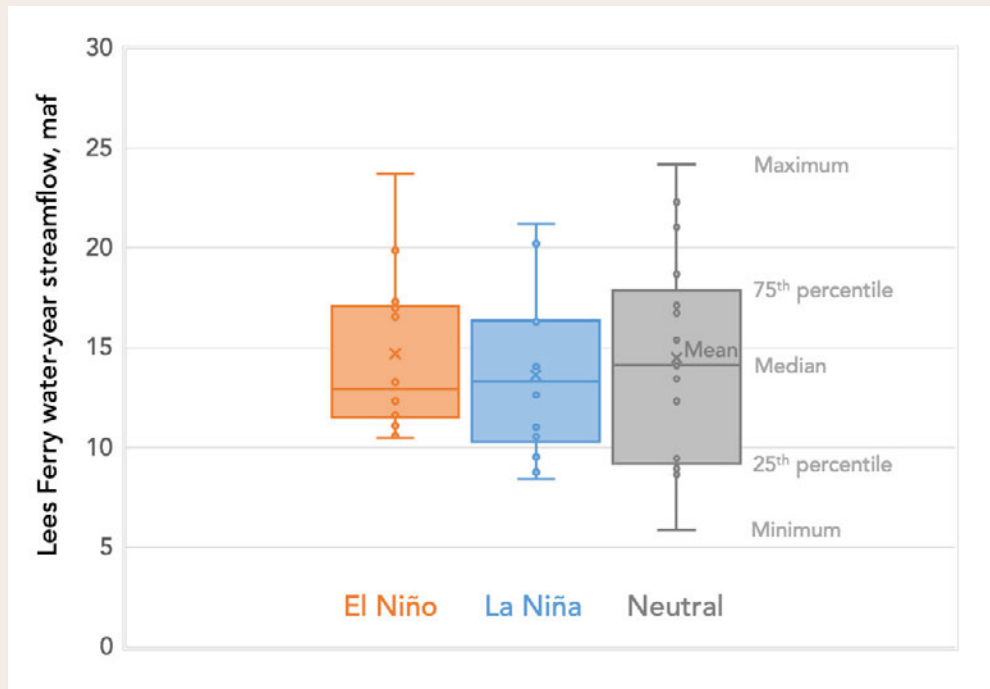


Figure 2.13

Upper Basin (Lees Ferry) water-year natural flows from 1980–2018, split into three ENSO categories: 12 fall El Niño cases, 12 fall La Niña cases, and 14 fall ENSO-neutral cases. El Niño conditions have been associated with higher average flow (“x” markers) than La Niña, but this difference is not statistically significant, nor are the differences from the average flow during ENSO-neutral years. (Data: Multivariate ENSO Index, K. Wolter; natural flows, Reclamation)

Decadal and multi-decadal oscillations

Pacific Decadal Oscillation (PDO)

In the north Pacific, to the north of the ENSO source region in the tropical Pacific, is the home of the Pacific Decadal Oscillation (PDO). The PDO was identified in the mid-1990s as the principal mode of sea-surface temperature variability in the northern Pacific. The PDO’s warm phase has positive (warmer-than-normal, El Niño-like) anomalies in the eastern North Pacific and negative (cooler-than-normal, La Niña-like) anomalies in the central and western North Pacific (Mantua et al. 1997). The main oscillation from warm to cool and back is irregular but usually has a period of 10–40 years, with occasional shorter excursions. The PDO is not a single well-defined physical phenomenon like ENSO, and much of the variation in the PDO may actually be ENSO variability translating to the northern Pacific over longer time scales (Newman, Compo, and Alexander 2003; Newman et al. 2016; Chen and Wallace 2016). The ENSO dipole does appear to be strengthened when PDO is in the same phase as ENSO, so that the Southwest and the Lower Basin have had a stronger wet tendency during

warm PDO + warm ENSO (i.e., El Niño), and a stronger dry tendency during cold PDO + cold ENSO (La Niña) (Gershunov and Barnett 1998; Brown and Comrie 2004; Wise 2010). However, these climate influences of PDO do not appear to be stable over time, which argues against their use in hydroclimate forecasting (McAfee 2014; Wise 2015).

Quasi-Decadal Oscillation (QDO)

The Quasi-Decadal Oscillation (QDO), another Pacific atmosphere-ocean oscillation with similarities to ENSO and PDO, but at an intermediate frequency (9–12 years) and greater regularity, was identified in the early 2000s (Tourre et al. 2001). Like the PDO, it appears to modulate the activity of ENSO. A previously identified quasi-decadal periodicity in levels of the Great Salt Lake since the mid-1800s was found to be coherent with the QDO when a lag time representing hydrologic processes was included (Wang et al. 2011), enabling multi-year forecasts of Great Salt Lake levels, which have since been validated through one-half of a decadal cycle (Gillies et al. 2011; 2015). More recently, Wang et al. (2018), noting that the Upper Basin is adjacent to and atmospherically “downstream” of the watershed of the Great Salt Lake, and that the Upper Basin streamflow also has quasi-decadal periodicity, asserted that there is potential for decadal-scale Upper Basin prediction based on the QDO. However, as noted earlier and shown in Figure 2.7, the quasi-decadal periodicity in Upper Basin (Lees Ferry) streamflow is strongest over the 1980–2015 period, and relatively weak prior to 1980, and it is not clear whether there is a solid basis for using the quasi-decadal oscillation in basin hydroclimate forecasts.

Atlantic Multidecadal Oscillation (AMO)

The Atlantic Multidecadal Oscillation (AMO) (Schlesinger and Ramankutty 1994) is a slowly varying sea-surface temperature and pressure oscillation in the north Atlantic Ocean with an irregular 30–80-year cycle. A series of studies in the early 2000s (Gray et al. 2004; Hidalgo 2004; McCabe, Palecki, and Betancourt 2004) found that the positive (warm) phase of the AMO was statistically associated with increased risk of drought in the Upper Basin. A study using climate models found that the combination of negative PDO phase and positive AMO phase is the least favorable for moisture in the interior U.S. (Schubert et al. 2009).

The trouble with multi-decadal oscillations

Studies in the 2000s on the AMO, PDO and other oscillations raised hopes that observations and predictions of the AMO state, as well as PDO, could lead to better seasonal and longer hydroclimate forecasts for the basin (Reclamation 2007c). However, the physical mechanism by which the AMO actually affects conditions in the interior West is unclear, unlike with ENSO (Nowak et al. 2012). Like the PDO, the stability of the AMO’s climate teleconnections over time is questionable. Also as with the PDO, there have been very few cycles of warm and cold phases during the observational

period (since about 1900) to compare with basin hydroclimate indices. Statistical relationships that have been found during the past century may not be representative of future relationships, given the limited number of cases to draw from (Switanek and Troch 2011).

The search for mechanisms of predictability continues

The identification of ENSO and PDO influence on western U.S. hydroclimate has spurred additional studies to identify other potential teleconnections, mainly between gridded Pacific Ocean SSTs and pressure fields and various hydroclimatic indices. By examining statistical relationships among hundreds of variables, these exploratory analyses are at high risk of finding relationships (i.e., teleconnections) that are statistically significant over the period of analysis, but are not rooted in a robust physical mechanism and therefore fail to show predictive skill beyond the period of analysis.

Recently, a new teleconnection was identified between sea-surface temperature and atmospheric pressure anomalies in the southwest Pacific Ocean near New Zealand in the late summer and fall, and winter (November–March) precipitation in the southwestern U.S., including the Lower Basin (Mamalakis et al. 2018). The authors' proposed New Zealand Index (NZI) had generally higher correlations with Southwest winter precipitation than did typical ENSO indicators over the 1950–2015 period. They also noted the strength of the NZI relationship has increased over the entire analysis period, almost doubling. This latter finding indicates volatility in the NZI-Southwest climate relationship and the potential for it to return to statistical non-significance in the future. Also, it is not clear that the NZI has a physical mechanism distinct from ENSO. It is possible that the NZI could be an adjunct to ENSO indicators in statistical forecasts of Southwest winter precipitation, but much more thorough exploration of the teleconnection, including its behavior prior to 1950 and its linkage with ENSO, is needed.

While the search for new teleconnections will undoubtedly continue in the research community, the inconvenient truth appears to be that most of the variability in basin hydroclimate is not associated with oscillations or discrete patterns that would potentially provide predictability on one or more time scales. This does not mean that the skill in seasonal precipitation forecasts cannot be improved (see Chapter 7), but that the skill may have a lower ceiling than both researchers and water managers would like.

2.9 A closer look at basin drought

Having described the overall hydroclimatic variability in the basin, and the key climatic mechanisms associated with that variability, it is important to take a closer look at the lower tail of the distribution of annual

hydroclimatic conditions (i.e., drought), which is the principal recurrent management challenge for water suppliers.

Hydrologic droughts in the basin are generally initiated by below-normal precipitation in the cool season (October–April) due to weather patterns that suppress storm tracks over the headwaters of the Upper Basin. The resulting reduced snowpack produces below normal spring–summer runoff, with an earlier peak. Due to early meltout and the low precipitation leading to below normal soil moisture, the land surface can dry out earlier in the warm season than usual, increasing evaporative demand and creating a feedback toward further warming and drying of the surface. Depletion of soil moisture in a dry year can lead to below normal runoff in the following year even if the precipitation in the second year is near normal (Das et al. 2011).

Analyses of hydrologic drought are complicated by the need to identify meaningful measures and thresholds for what constitutes drought conditions, and thus when droughts begin and end, and their severity over space and time. Which measures and thresholds are meaningful depends on the specific application context. This is especially true for the Colorado River system, in which total consumptive use plus other depletions typically exceeds supply, such that under even average hydrologic conditions the levels of Lake Mead and Lake Powell will tend to decline. The recent declines in mainstem reservoir storage reflect both direct drought impacts and the system imbalance between supply and depletions, and it is difficult to disentangle the two factors. To assess the nature of recent drought conditions, it may be more meaningful to look at natural inflows to the system, such as those estimated at the Lees Ferry gage, than at reservoir levels.

In the water supply analysis in Reclamation (2020) a “streamflow deficit” (i.e., drought) was defined as a two-year average flow less than 15 maf at Lees Ferry. The 2-year averaging acknowledges the buffering capacity of system reservoir storage. By this measure, the most severe drought in the observed record was from 2000–2005 (6 years), with a cumulative deficit of 24 maf, exceeding the 7-year droughts in the 1930s and 1960s, in which the deficits were about 18 maf. There was another 6-year drought from 2012–2017, with a cumulative deficit of 13 maf (Figure 2.14). Multi-year streamflow deficits of greater than 10 maf are clearly a recurrent feature of the basin’s hydroclimate, but the period since 2000 appears highly unusual in that it includes two such droughts: the most severe (2000–2005) and the 5th most severe (2012–2017).

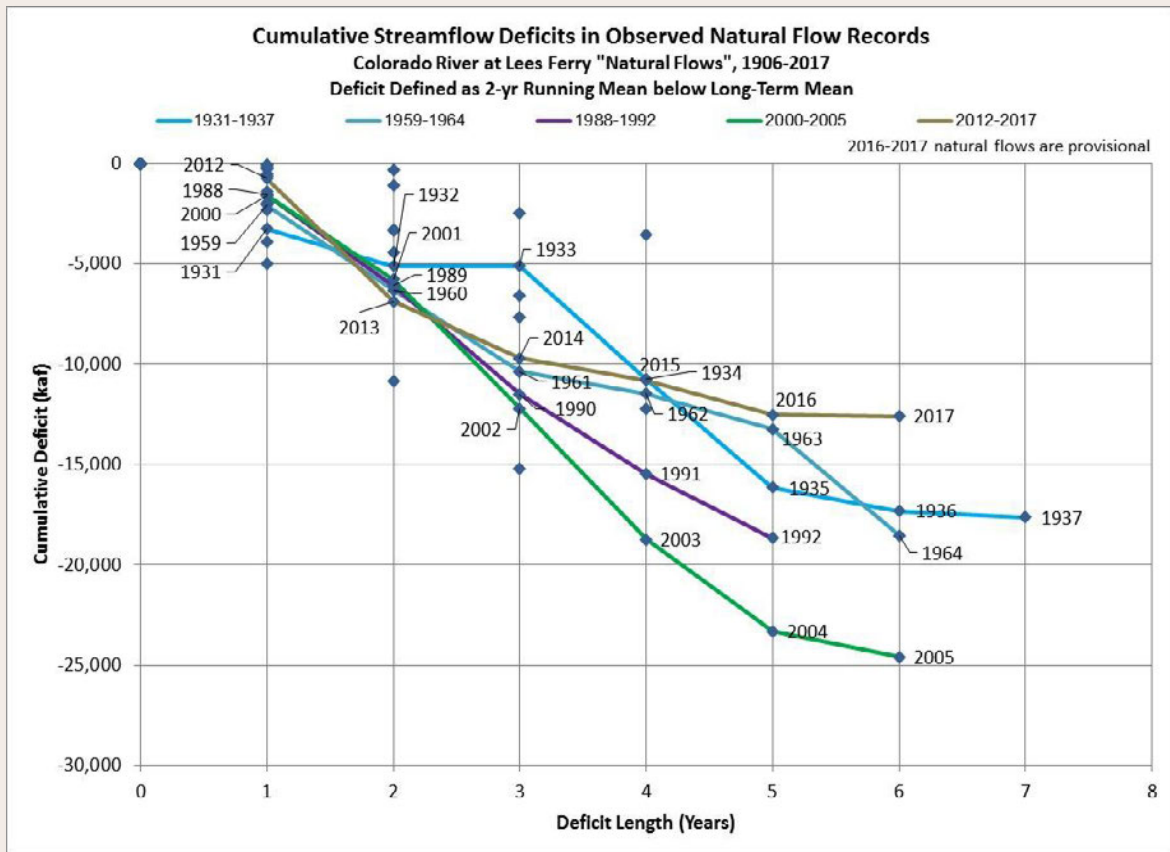


Figure 2.14

Cumulative streamflow deficits (defined as 2-year running mean below 15 maf) for the Colorado River at Lees Ferry, Arizona, with the five longest and most severe droughts (2000–2005, 2012–2017, 1988–1992, 1959–1965, 1931–1937) highlighted. (Source: Reclamation 2020)

Woodhouse (2012) analyzed the atmospheric and oceanic features associated with six multi-year Upper Basin droughts from the 1930s to the 2000s, using a different drought definition than shown in Figure 2.14. Her analysis showed that each extended drought evolves in a unique way. The onset and persistence of some droughts is linked to La Niña events, while in other cases, drought years coincide with El Niño events. Most critically, past multi-year droughts have persisted through a variety of modes of natural variability. A key feature for drought years not associated with La Niña events has been a high-pressure anomaly centered over the Pacific Northwest, which tends to deflect storm tracks away from the Upper Basin.

The water supply analysis in the “Colorado River Basin Water Supply and Demand Study” (hereinafter “Basin Study”; Reclamation 2012e) examined the streamflow reconstruction by Meko et al. (2007) and compared the distribution of the reconstructed streamflow deficits during the historical period (1906–2005) with the distribution of reconstructed streamflow deficits (droughts) over the entire reconstruction (762–2005). That analysis showed that most droughts are 3 years or shorter (Figure 2.15). The distribution of deficits over the 20th century is similar to the distribution over the entire >1200-year period, except at the tails; i.e., events of very long duration or high severity, or both. Over the full reconstruction period, droughts with estimated durations of greater than 5 years and estimated cumulative deficits of greater than 15 maf were much more frequent than in the 1906–2005 period.

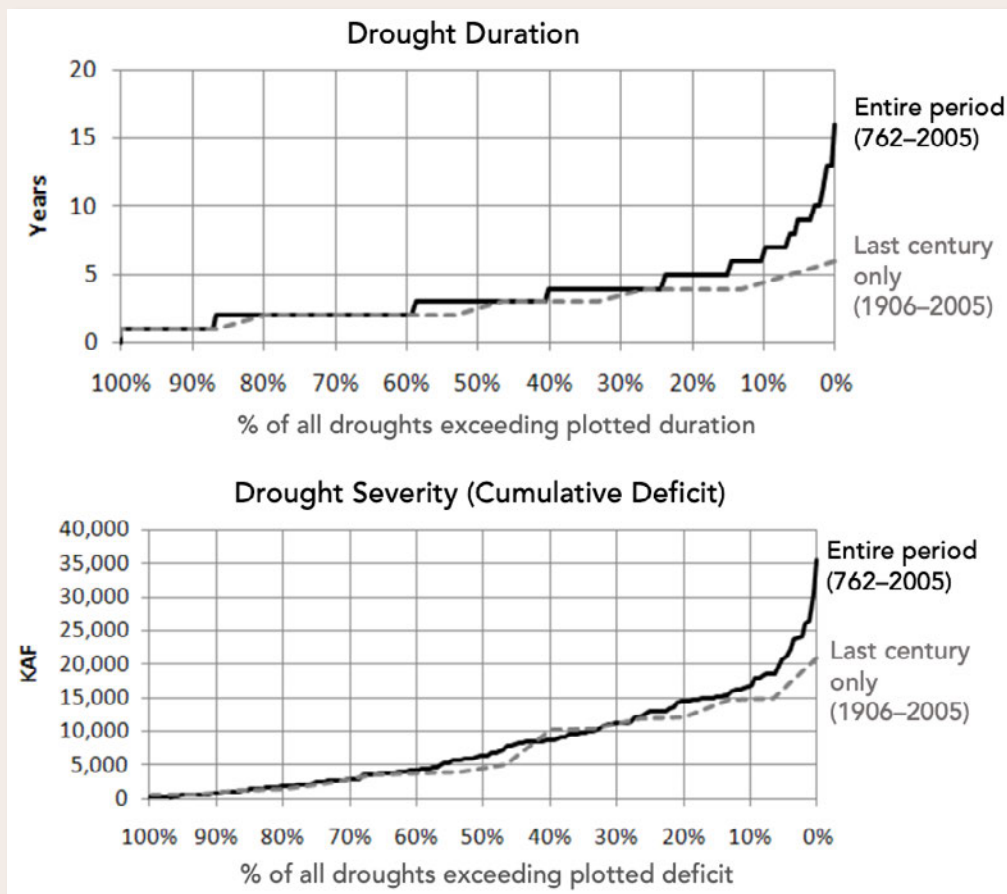


Figure 2.15

Drought characteristics over the most recent century (dashed gray line) from the Meko et al. (2007) tree-ring reconstruction of Lees Ferry natural flows, compared with the full reconstructed period (762–2005; solid black line). The full reconstruction contains extreme droughts with longer durations and larger cumulative deficits, as indicated by increasing divergences at lower exceedance probabilities (<10%). (Source: adapted from Reclamation 2012b)

2.10 Recent hydroclimate trends and likely causes

The most prominent hydroclimatic change in the basin over the past 40 years has been a substantial warming trend. Trends in precipitation are more difficult to discern. Changes in snowpack, runoff volume, and runoff timing have been observed and these can be linked, at least in part, to the warming trend. The recent trends in these and other variables for the Upper Basin specifically are summarized in Table 2.3.

Table 2.3

Summary of recent hydroclimate trends in the Upper Basin and the likely causes of those trends. See text in the sections below for references.

Variable	Trend since 1980s	Likely causes, in order of importance
Temperature	Increasing*	Anthropogenic climate change, natural variability
Precipitation	Decreasing	Natural variability, anthropogenic climate change
Snowpack water volume (April 1 SWE)	Decreasing*	Decreasing precipitation, warming temperatures
Timing of snowmelt and runoff	Earlier*	Warming temperatures, dust-on-snow, decreasing precipitation
Annual streamflow	Decreasing	Decreasing precipitation, warming temperatures

* Trend has been found to be statistically significant for part or all of the Upper Basin by one or more studies

Temperature

The most conspicuous feature of the observed record of annual temperatures for the basin is the warming trend in recent decades (Figure 2.16), as highlighted in many previous reports and studies (National Research Council 2007; Reclamation 2012e; Nowak et al. 2012). Since 1980, there has been a persistent and statistically significant warming trend of about +0.5°F per decade in both the Upper and Lower Basins, with a total of 2.0°F of warming during the 40-year period of 1980–2019. In the Upper and Lower Basins, and over the entire basin (Figure 2.16), 2009–2018 was the warmest 10-year period in the record, and 2017 was the warmest single year. Of the 20 warmest years on record, 17 have occurred since 1994. While the upward trend has included both warmer and cooler years, every year since 1994—including relatively cool 2019—has been warmer than the 1970–1999 average. The average temperature since 2000 has been 2.0°F warmer than the 20th-century average.

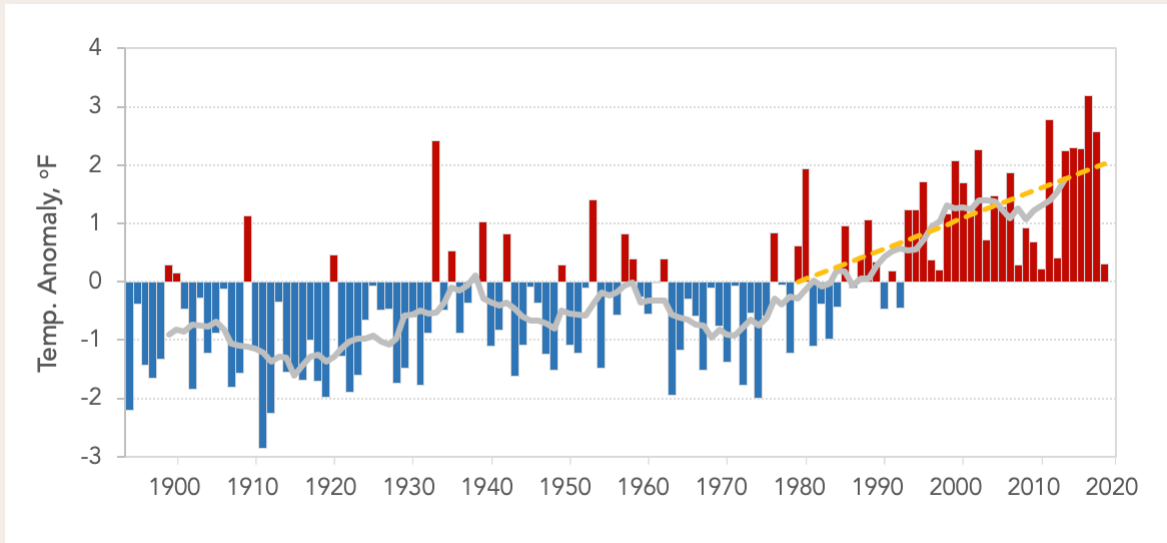


Figure 2.16

Annually averaged temperature for the Colorado River Basin, 1895–2019, shown as departures from a 1970–1999 average. The gray line is a 10-year running average plotted on the 6th year. A 40-year linear trend (dashed yellow line) shows 2.4°F of warming from 1980–2019. (Data: NOAA NCEI)

This warming has been observed in all seasons, with seasonal trends (+0.4°F to +0.7°F per decade) similar to those for annual temperatures. Daily maximum temperatures have warmed more (+0.65°F per decade) than the average temperatures (+0.5°F per decade) or the daily minimum temperatures (+0.4°F per decade). It is not clear whether the magnitude of warming has differed between lower and higher elevations within the basin (Lukas et al. 2014).

Paleoclimatic reconstructions of temperature for locations within, or regions that include, the Colorado River Basin all indicate that the period since 1950 has been warmer than any time in the past 600 years, and that more recent temperatures, since 2000, are warmer than at any time in the past 2000 years (Hoerling et al. 2013).

The warming trend for the basin since 1980 (+2.0°F) mirrors persistent warming trends seen over the same time period over the 11 western states (+1.7°F), the conterminous U.S. (+1.7°F), and the entire globe (+1.2°F). At the global scale, strong indications from multiple lines of evidence have led to the conclusion that it is extremely likely (>95% probability) that human influence through greenhouse gas emissions and other sources has been the dominant cause of the observed warming over the late 20th century and the 21st century (USGCRP 2017). Similarly, human influence has been detected in the observed warming trends for North America as a whole, and

for the northern and western regions of the U.S., including the Colorado River Basin (USGCRP 2017).

Precipitation

As shown previously (Figure 2.6), observed annual (water year) precipitation for the basin is far more variable on interannual time scales than temperature. For multi-decadal trends to statistically emerge from the background noise of this high variability, they would need to be large. While a straight-line fit to the 1980–2019 period for the Upper Basin does indicate lower average annual precipitation in more recent years, this declining trend is not statistically significant. The unusually high precipitation values in the 1980s means that any trend that starts in the vicinity of 1980 will tend downward. Importantly, the average annual precipitation over the past 20 years (2000–2019) does not stand out relative to periods of the same length earlier in the observed record. A declining but non-significant trend is also seen in Lower Basin annual precipitation over the 1980–2019 period. Looking at only cold-season (Oct–Mar) precipitation, the percentage declines over the 1980–2019 period in both the Upper and Lower Basins are greater than the declines for annual precipitation. But as with annual precipitation, the overall, below-average, cold-season precipitation from 2000–2019 is not an outlier in the context of the full observed record.

Detection and attribution analyses for recent multidecadal periods indicate that the generally lower precipitation seen in the southwestern U.S., including the Colorado River Basin, in recent decades was likely caused by natural variability, and not human-caused climate change (Barnett et al. 2008; Hoerling, Eischeid, and Perlwitz 2010; Lehner et al. 2018). New analyses using global climate models suggest that human-caused climate change is exerting a long-term tendency toward reduced precipitation in the region that includes the Colorado River Basin, though this tendency is small enough to be overwhelmed by natural variability, and is undetectable from the observed record of precipitation alone (Guo et al. 2019; Hoerling et al. 2019).

Snowpack

The peak water volume of the basin snowpack (e.g., April 1 SWE) is mainly determined by the amount of cold-season precipitation, but it can also reflect weather factors that lead to more or less snow loss (sublimation and melt) than usual during the cold season. Observations of SWE are available for portions of the basin since the 1930s and with much greater coverage over the basin starting in the late 1970s. These SWE records show interannual and decadal-scale variations in the regional snowpack that closely match the fluctuations in cold-season precipitation.

In the mid-2000s, several studies reported declining trends in April 1 SWE at most SNOTEL and snow course measurement sites throughout the

western U.S. (Hamlet et al. 2005; Mote et al. 2005; Regonda et al. 2005). These studies linked the declining SWE trends with warming spring temperatures throughout the West, with a key mechanism being an increasing fraction of cold-season precipitation falling as rain instead of snow as temperatures have increased (Knowles, Dettinger, and Cayan 2006). In the Colorado River Basin, declining SWE trends were generally weaker, or mixed with increasing trends, compared to other regions of the western U.S because winter temperatures are well below freezing, reducing the impact of this broader snow-to-rain shift (Hamlet et al. 2005; Knowles, Dettinger, and Cayan 2006). Later analyses specific to western Colorado also found declining trends in April 1 SWE, over the 1978–2007 period (Clow 2010), and over 30-, 50-, and 70-year periods ending in 2012 (Lukas et al. 2014). Clow (2010) partially attributed the decline in April 1 SWE to decreasing winter precipitation observed over the same period, also identifying a role for increasing spring temperatures.

Newer analyses have reinforced that the observed declining trends in April 1 SWE in the western U.S. are substantial and pervasive (Mote et al. 2018; Zeng, Broxton, and Dawson 2018; Fyfe et al. 2017). These analyses also report somewhat greater changes to snowpacks in the Colorado River Basin over the last several decades than was reported in the older studies. All of these studies indicate a role for warming temperatures in explaining the declining SWE, though they also suggest that recent precipitation trends have played an important role. A study that assessed the trends in April 1 SWE across the West from 1984–2018 assigned greater importance to warming, finding that the declining SWE trends in the Upper Basin over that period were of roughly the same magnitude that would be expected from warming alone (Siler, Proistosescu, and Po-Chedley 2019). Two studies that analyzed gridded spatially explicit SWE datasets (see Chapter 5) found larger SWE declines than one would infer from SNOTEL sites alone, indicating that lower-elevation snow below most of the SNOTEL network has experienced greater changes than higher-elevation snow (Fyfe et al. 2017; Zeng, Broxton, and Dawson 2018). Another recent study shows that these reductions in peak (April 1) SWE are one element of systemic changes to the seasonal snowpack accumulation and melt curves (e.g., Figure 2.4); across the western U.S., these curves are becoming significantly narrower and less skewed over time, indicating later onset of accumulation, earlier onset of melt, consequently slower melt, and shorter duration of snow cover (Evan 2018).

To summarize the studies of snowpack in the western U.S. and corresponding conclusions for the Colorado River Basin: (a) April 1 SWE has declined over the past 35–60 years across most of the basin headwaters, and some of these declining trends are statistically significant; (b) at least a portion of the April 1 SWE decline in the basin is attributable to warming temperatures since the late 1970s, with a contribution from the decline in

cool-season precipitation during the most recent decades, which itself is likely due to natural variability; (c) because of the relatively cold winter climate of the Upper Basin's headwaters, the snowpack is more resistant to warming-related impacts than most other regions of the West, and (d) within each sub-basin, lower elevations have generally seen larger reductions in April 1 SWE than higher elevations.

Timing of snowmelt and runoff

While the timing of peak spring runoff is not as important as the runoff quantity to overall basin water system outcomes due to the large system storage capacity, particular water uses can be sensitive to runoff timing, especially direct diversion for irrigation, and the variation and trends in the shape of the annual hydrograph can have implications for reservoir operations. The timing of snowmelt in the basin headwaters and peak runoff naturally varies from year to year, depending mainly on the size of the snowpack and the particular trajectory of the weather during the spring. Smaller snowpacks tend to become isothermal (i.e., reach 32°F throughout the snow column)—a precondition for rapid melt—earlier, and melt out earlier, than larger snowpacks. Persistent dry, sunny, spring weather—which is more likely to occur in low-snow years—will accelerate meltout, while frequent spring storms—more likely to occur in high snow years—will delay meltout. Snowpack size (e.g., April 1 SWE) and snowmelt and runoff timing are thus physically linked as well as observationally linked; a consistent shift in the timing of peak SWE and melt onset to dates earlier than April 1 will also register as a decline in April 1 SWE, even if peak seasonal SWE (SWE_{max}) does not decline.

Given the findings of widespread declines in April 1 SWE as described above, it is unsurprising that multiple studies since the early 2000s that have specifically examined the timing of snowmelt and runoff in parts or all of the western U.S. have found widespread trends toward earlier snowmelt and runoff over the past 3–6 decades (Stewart, Cayan, and Dettinger 2005; Regonda et al. 2005; Clow 2010; Fritze, Stewart, and Pebesma 2011; Hoerling et al. 2013; Pederson, Betancourt, and McCabe 2013). The Evan (2018) study described above also confirms the general shift toward earlier snowmelt. For the Upper Basin in particular, the more recent of these studies have detected progressively larger and more pervasive shifts toward earlier spring runoff onset and peak runoff. Clow (2010) found shifts toward earlier snowmelt and runoff timing in western Colorado of 1–4 weeks from 1978 to 2007. Similarly, Hoerling et al. (2013) found that for 13 of 17 gages in the Upper Basin, average runoff timing for 2001–2010 was earlier, by 1–3 weeks, than the average runoff timing for 1950–2000.

As with the trends in April 1 SWE, it is difficult to separate the likely causes of the shift toward earlier snowmelt and runoff. Warming winter-spring temperatures almost certainly have a role, but the decline in cold-season

precipitation since 2000 appears to be an important driver as well. Episodic dust-on-snow deposition also causes earlier snowmelt and runoff (Chapter 5; Painter et al. 2007; 2010; Deems et al. 2013). Snowpacks in the Upper Basin have become generally dustier in recent decades, with especially large effects on snowmelt and runoff timing in the San Juan Basin (Clow, Williams, and Schuster 2016; Painter et al. 2018).

Streamflow volumes and runoff efficiency

Among the indicators of hydroclimatic variability and change, annual streamflow volumes are the most directly relevant to basin water management and water use. Annual streamflow also integrates multiple processes and effects that play out over different temporal and spatial scales, complicating evaluation of the sources of variability and change.

As basin water managers and water users are well aware, the period since 2000 has seen overall below-average Upper Basin (Lees Ferry) flow volumes, with an average naturalized flow of 12.6 maf/year from 2000–2019, which is 15% below the long-term average of 14.8 maf (1906–2019). (Average flow from 1999–2018 was marginally lower than from 2000–2019.) The next lowest 20-year period of flow is 1950–1969, which averaged 13.0 maf/year. The cumulative streamflow deficit of roughly 47 maf since 2000 relative to the long-term average accounts for a large portion of the current drawdown of Lakes Powell and Mead. The declining trend in Lees Ferry natural flows from 1980–2019 is almost statistically significant ($p = 0.06$), and this trend is larger, compared to interannual variability, than the trend in Upper Basin water-year precipitation over the same period. However, even larger declining trends in Lees Ferry flows were observed over 40-year periods beginning in the 1910s and ending in the 1950s, so this recent decline is not unprecedented.

Unlike Upper Basin natural flows, the available flow data for the Lower Basin is primarily gaged flows, or the net gain in flow between gages (see Chapter 5), so the following trends may reflect impacts from human activities. The total inflows between Lees Ferry and Lake Mead show a downward trend similar to that for the Upper Basin, with an average of 1.02 maf/year from 2000–2016, 20% less than the long-term average of 1.23 maf/year (1906–2016). Within that overall number, the gaged inflows from the four tributaries show the following departures for 2000–2016 relative to the long-term mean: Paria River, -15%; Little Colorado River, -40%; Virgin River, -10%; and the Bill Williams River, -41%.

As discussed previously in this chapter, the variability in water-year precipitation is the most important driver of variability in annual streamflow. The period of reduced Upper Basin flow since the 2000s and the overall declining trend in flow since the late 1970s has coincided with a decline in water-year precipitation as described earlier. The consensus of

recent studies is that roughly half or more of the recent low-streamflow anomaly (since 2000) is due to variability and trends in precipitation (Nowak et al. 2012; Udall and Overpeck 2017; C. A. Woodhouse et al. 2016; McCabe et al. 2017; Barsugli and Livneh 2018; Xiao, Udall, and Lettenmaier 2018; Hoerling et al. 2019).

But it is also clear that warming temperatures can lead to long-term reductions in streamflow. Hydrologic modeling has been used to put a range of values to the general expectation that runoff in the Colorado River Basin decreases with increasing temperatures. An analysis by McCabe and Wolock (2007) using their relatively simple water-balance model for the Upper Basin indicated a 5% decline in Upper Basin runoff per 1°F of warming. Intercomparisons using more sophisticated hydrologic models (see Chapter 6) calibrated for the basin hydrology indicate a 1.5% to 6% decrease (model average: 3.5% decrease) in Upper Basin runoff per 1°F of regional warming (Vano, Das, and Lettenmaier 2012; Vano and Lettenmaier 2014). Based on this range of modeled temperature sensitivities of runoff, Udall and Overpeck (2017) concluded that approximately one-third (range: 17-50%) of the Lees Ferry streamflow departure from 2000–2014, relative to the 20th-century average, was due to the effects of the warming alone, with the remainder due to decreased precipitation during the 2000–2014 period.

Three more recent model-based studies, using different methodologies, came to conclusions at opposite ends of the range outlined by Udall and Overpeck (2017). Xiao, Udall, and Lettenmaier (2018), based on simulations of historical hydroclimate with the Variable Infiltration Capacity hydrologic model (see Chapter 6), concluded that a little more than one-half (54%) of the Lees Ferry streamflow departure from 2000–2014 was due to warming alone. Milly and Dunne (2020), using a different hydrologic model, also estimated that just over half of the 2000–2017 Lees Ferry streamflow departure was due to warming alone, and that the temperature sensitivity of runoff was about 5% per 1°F of regional warming. But based on simulations from three global climate models (GCMs) with embedded hydrology (or land surface) models, Hoerling et al. (2019) estimated that the temperature sensitivity of runoff was about 1.5% per 1°F of regional warming, and that about 20% of the Lees Ferry streamflow departure since 2000 was due to warming.

The warming effect on Upper Basin runoff has also been detected and quantified directly from the observational record, while taking into account the potentially confounding relationship between precipitation and temperature. Regression analysis by Nowak et al. (2012) indicated a 7.5% reduction in annual Upper Basin runoff for every 1°F warming, a larger reduction than shown by any of the hydrologic models. McCabe et al. (2017), using a similar regression analysis, concluded that the impact of warming temperatures on Upper Basin runoff was -7% for the period from the late

1980s through 2012, which implies a 4–5% reduction in annual runoff per 1°F warming, within the range found with the hydrologic models.

Woodhouse et al. (2016) inferred an impact of warm-season temperatures on Upper Basin runoff in recent decades from the increasing differences between the precipitation anomaly and the runoff anomaly, but did not quantify the impact.

To summarize, compared with a decade ago, there is now substantial evidence from both hydrologic model experiments and analyses of the observed record that recent warming temperatures have already had a role in reducing Colorado River flows. Those studies also indicate that the magnitude of the incremental impact of climate warming on streamflow remains uncertain. This mirrors the consensus of participants at a recent workshop on understanding the causes of the historical changes in flow of the Colorado River (Barsugli and Livneh 2018). The workshop report also underscored that a key challenge in quantifying the role of temperature is the uncertainty in the observed records of temperature and especially precipitation, which is much more spatially and temporally variable than temperature. The most runoff-productive mountain areas have relatively sparse observations, and the different gridded climate datasets used to calibrate hydrologic models and in other analyses can have substantial differences over these mountain areas (see Chapter 4; Barsugli and Livneh 2018). For that matter, the record of naturalized runoff for the Upper Basin (Lees Ferry) used for many of these analyses has uncertainties that are not well quantified or broadly appreciated within the research and application communities (see Chapter 5).

Other recent studies, using both hydrologic models and field observations, have focused on the mechanisms by which warming acts to reduce Colorado River streamflows, including those mechanisms described earlier as impacting the snowpack. Following the seasonal sequence of events, these mechanisms include:

- Fall (and spring) precipitation increasingly comes as rain instead of snow, which reduces runoff efficiency (Berghuijs, Woods, and Hrachowitz 2014).
- Sublimation losses from snowpacks during the winter and spring are higher due to the warmer, “thirstier” atmosphere (Foster et al. 2016).
- Snowmelt initiates earlier in the spring, which leads to slower average melt rates (see Figure 2.4), which reduces runoff efficiency (Barnhart et al. 2016).
- The earlier meltout exposes soils earlier in the warm season, increasing the absorption of solar radiation at the land surface and leading to increased seasonal evaporation (Deems et al. 2013, Milly and Dunne 2020).

- The growing season for natural vegetation and crops starts earlier and lasts longer, leading to increased seasonal transpiration (Deems et al. 2013).
- Evapotranspiration rates generally increase with warmer temperatures (Foster et al. 2016; Milly and Dunne 2020).

The energy budget changes (i.e., increase in sublimation and evapotranspiration) appear to be a more important contributor to the overall temperature effect on runoff in the basin than the phase change in precipitation from snow to rain (Foster et al. 2016). This is consistent with other modeling analyses that have examined the seasonal dimension of temperature's effects; those studies have indicated that warming during the warm season (April–September) is much more effective at reducing runoff than warming of the same magnitude during the cold season (October–March) (Das et al. 2011; McCabe et al. 2017).

2.11 Challenges and opportunities

The most pressing challenges in our understanding of the historical and recent hydroclimate of the Colorado River Basin regard the recent changes in the key variables described in the previous section. Better quantification of these trends (*how much* things have changed), and more confident attributions of them to the respective causal factors (*why* things have changed), would facilitate greater inclusion of these changes in short-term and mid-term forecasting (Chapter 8) and long-term planning (Chapters 9–11).

Challenges

- There is still considerable uncertainty in the quantification of the relative roles of temperature, precipitation, antecedent soil moisture, dust-on-snow, and vegetation change in recent and ongoing variability and change in Upper Basin snowpack and streamflow.
- These factors have substantial spatial variability, but most studies have conducted analyses and presented findings only at the Upper Basin-wide scale (e.g. Lees Ferry).

Opportunities

- Conduct analyses of Upper Basin hydrologic change that are spatially disaggregated at least to the eight major sub-basins (Upper Green, Yampa-White, etc.), or focus only on the most productive headwaters areas, or both.
- Pursue the various pathways to improve hydrologic modeling presented in Chapter 6.
- Conduct intercomparisons of hydrologic models and statistical methods for assessing the factors behind hydrologic changes.



Chapter 3

Primary Planning Tools

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Key points

- Three monthly Reclamation models, developed in RiverWare™, support planning at three time scales: short-term (up to 24 months), mid-term (up to 60 months), and long-term (multiple decades).
- The models use rules to incorporate operational policies set forth in Records of Decisions and other operational agreements, and some long-term studies also explore potential alternative policies.
- Hydrologic inputs to the short-term and mid-term models are either flows forecast by the NOAA Colorado Basin River Forecast Center (CBRFC) or statistical averages of observed flows.
- Hydrologic inputs to the long-term model may be based on historical hydrology, paleohydrology, climate change-informed hydrology, or hybrids.
- Measured Upper Basin water demands for the short-term and mid-term models are accounted for in the CBRFC's forecast; Lower Basin water demands are provided by Lower Basin water users and Mexico. Both Upper and Lower Basin demands for the long-term model are based on projections supplied by water users.
- Uncertainties, errors, and limitations arise from input data sources, assumptions about the future, and necessary simplifications of a complex water supply system.

3.1 Introduction

Planning and operations models support decision making by providing computer-based representations of water supply systems that allow analysis of a variety of hydrologic, operational, administrative, and infrastructure scenarios. They are designed to represent systems with networks of inflows, uses, and storage that serve multiple objectives, and they are built to generate or accept large databases of streamflow data. These models track the movement and storage of water through river reaches, reservoirs, canals, and other infrastructure, and account for withdrawals and gains and losses. They usually simulate operations and the administrative rules that govern water allocation.

World-wide, a number of generalized modeling tools have been used to simulate large scale river basin systems. There are differences and similarities among the tools in core solver type and the kinds of processes simulated, but most of them are flexible as to time step, spatial extent, resolution, and operations. They have advantages and limitations that make them more or less suitable for particular analyses. For more information about generalized, river basin system modeling tools, and some in-depth comparisons, see Wurbs (1994; 2012); Stratus Consulting (2005); Zagona (2010); US Army Corps of Engineers (2012); Johnson (2014); California Dept.

of Water Resources (2016; 2019); Colorado State University (2017); DHI (2019); Lynker (2019); SEI (2019); Texas A&M University (2019a; 2019b).

3.2 Reclamation's models

Reclamation manages the system reservoirs on the Colorado River within the legal and political framework captured in a body of documents known as “the Law of the River” (Nathanson 1978; Reclamation 2007e; 2015b). The Law of the River specifies Colorado River entitlements and priorities and comprises numerous operating criteria, regulations, and administrative decisions included in federal and state statutes, interstate compacts, court decisions and decrees, an international treaty, and contracts with the Secretary of Interior. As such, modeling undertaken by Reclamation to support basin management must be able to represent both the challenging institutional setting and the complex physical system. The results of modeling studies are a familiar, standardized foundation for Reclamation's stakeholder outreach and in some instances are the basis for determining official operations. The core of this modeling is a mass balance calculation that accounts for water entering the system, water leaving the system (e.g., from consumptive use of water, trans-basin diversions, evaporation), and water moving through the system (i.e., either stored in reservoirs or flowing in river reaches).

Since the 1990s, Reclamation has developed system models using RiverWare™, an object-oriented, generalized river basin modeling platform developed in partnership with the University of Colorado's Center for Advanced Decision Support for Water and Environmental Systems (CADSWES) and the Tennessee Valley Authority (Biddle 2001; Zagona et al. 2001).

Reclamation's three basin-wide planning and operations models are the 24 Month Study (24MS), the Mid-Term Probabilistic Operations Model (MTOM), and the Colorado River Simulation System (CRSS). The three models and their applications are summarized in Figure 3.1.

RiverWare Operations Model	Time Horizon	Primary Use
24-Month Study Model (24MS)	1-2 years	Annual Operating Plan tier determinations and projections of current conditions
Mid-term Probabilistic Operations Model (MTOM)	1-5 years	Risk-based operational planning and analysis
Colorado River Simulation System (CRSS)	Decades	Long-term planning studies, criteria development, and risk analysis

Figure 3.1

Reclamation's basin-wide planning and operations models (Source: adapted from Fulp 2003)

The core elements that characterize the three models are listed below.

- Purpose
- Time step and simulation horizon
- Structure and resolution
- Physical processes (evaporation and bank storage)
- Inputs
 - Initial reservoir conditions
 - Operational policies
 - Future water use/demand
 - Future inflows
- Outputs (variables, deterministic vs. probabilistic)

All three models run on a monthly time step, use the same methods to estimate reservoir evaporation and bank storage (monthly coefficients applied to surface area and single coefficients applied to total reservoir storage, respectively), and represent the same operating policies, but are otherwise different in multiple respects.

RiverWare supports “rule-based” simulation (Zagona 2010), in which logic statements, rather than hard-coded values, are used to represent operational policy. This capability makes RiverWare well suited to simulate the requirements stipulated by the Law of the River. A simple rule might take the form of “If Reservoir A elevation is x , and forecast inflow is y , then make release z .” An example of a RiverWare rule that might be executed in a Colorado River simulation is provided in Figure 3.2.

The “objects” in RiverWare’s object-oriented modeling system may be reservoirs, river reaches, stream confluences, diversions, inflows, canals, pipelines, gages, or other water resources features (CADSWES 2018). Each object is assigned attributes ranging from its capacity to its representation of physical processes. Water flows between objects via links, but mass balance is calculated at the object level.

Each model is described in detail in the sections that follow, organized from shortest to longest time scale.

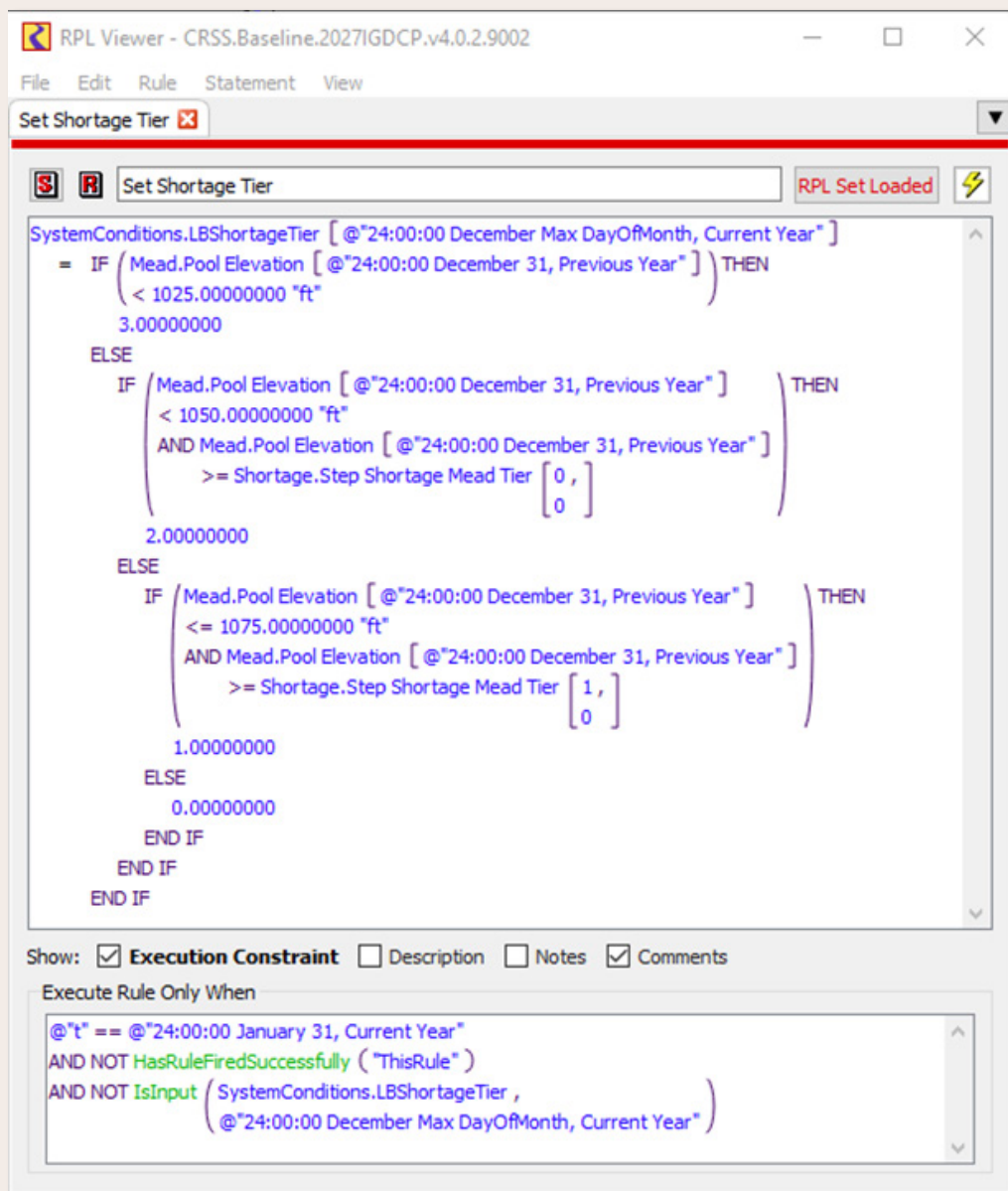


Figure 3.2

Sample rule from CRSS as implemented in RiverWare (Source: Reclamation)

24-Month Study Model (24MS)

The 24-Month Study model (24MS) is an operations model developed by Reclamation to support planning for the upcoming 24 months. 24MS began as a FORTRAN program, was re-implemented in RiverWare in 1997, and continues to be refined to better represent the physical system and evolving operational policies.

The model is run every month to provide basin-wide operational updates as hydrology and demand projections evolve. The August modeling results are used to determine the annual operating conditions for Lake Powell and Lake Mead for the upcoming year as reported in Reclamation's Annual Operating Plan for Colorado River Reservoirs (AOP). Under certain conditions, the April modeling results may prompt adjustments to Powell operations. The operating tiers for Lake Powell and Lake Mead determine release volumes from Lake Powell, and also whether and by how much deliveries from Lake Mead to Lower Basin water users and Mexico will be reduced (under shortage conditions) or supplemented (under surplus conditions). Operational tiers, release volumes, and water delivery conditions were set forth in the 2007 Interim Guidelines (U.S. Secretary of the Interior 2007) and Minute 319 (International Boundary and Water Commission 2012), and were more recently augmented and extended by the Drought Contingency Plan (DCP; Reclamation 2019c) and Minute 323 (International Boundary and Water Commission 2017). Per the Interim Guidelines, the August 24MS projections of January 1 reservoir elevations determine the operating tiers for Lakes Powell and Mead for the upcoming calendar year. Subsequent April 24MS projections of September 30 elevations of Lakes Powell and Mead may result in an adjustment to the annual release volume from Lake Powell.

The structure of 24MS is driven by its core purpose, which is to simulate operations at 12 Reclamation reservoirs. Each 24MS simulation is initialized with current reservoir elevations (conditions from the last day of the previous month). Every time 24MS is run, Reclamation employees in the Upper and Lower Colorado regional reservoir operations offices input projected reservoir operations by hand. This manual approach takes advantage of the expertise of reservoir operators and obviates the need for reservoir operations logic in the model but limits the ability to incorporate operational and hydrologic uncertainty (discussed below and in Reclamation 2015a). The model is not exclusively manual input—in years 2 and 3 of the 24MS simulation, Lower Basin operations are automated and driven by rules that reflect projected operating conditions for Lake Mead.

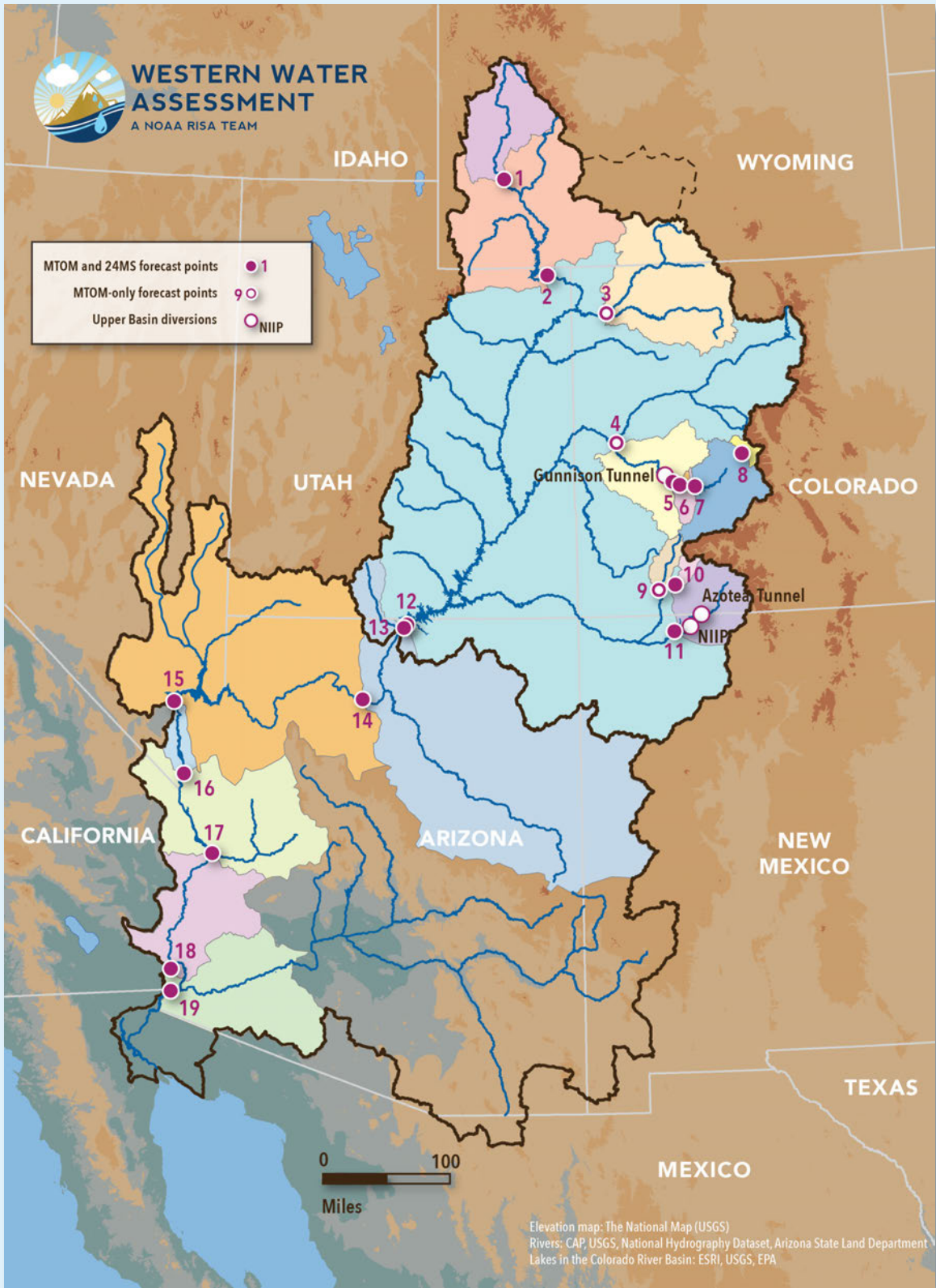


Figure 3.3

Map of sub-basins and forecast points for 24MS and MTOM. The basins in the map are color-coded to match the sub-basins shown in Table 3.1. (Source: Reclamation)

Table 3.1

Sources of inflows used in 24MS and MTOM. The cells in the table are color-coded to match the sub-basins shown in Figure 3.3. (See additional explanation below; Source: Reclamation)

CRSS natural flow point	USGS Gage Name	USGS Gage #	Relevant 24MS/MTOM forecast sub-basin	Relevant MTOM/24MS forecast point
1	Colorado River At Glenwood Springs, CO	09072500	Lake Powell	12
2	Colorado River Near Cameo, CO	09095500		
3	Taylor River Below Taylor Park, CO	09109000	Taylor Park Reservoir	8
4	Gunnison River Below Blue Mesa, CO	09124700	Blue Mesa Reservoir	7
5	Gunnison River At Crystal , CO	09128000	Crystal Reservoir	5
			Morrow Point Reservoir	6
6	Gunnison River Near Grand Junction, CO	09152500	Gunnison R. gains Crystal to Grand Junction*	4*
7	Dolores River Near Cisco, UT	09180000	Lake Powell	12
8	Colorado River Near Cisco, UT	09180500		
9	Green R Bel Fontenelle Res, WY	09211200	Fontenelle Reservoir	1
10	Green R. Nr Green River, WY	09217000	Flaming Gorge Reservoir	2
11	Green River Near Greendale, UT	09234500		
12	Yampa River Near Maybell, CO	09251000	Yampa River at Deerlodge Park*	3*
13	Little Snake River Near Lily, CO	09260000		
14	Duchesne River Near Randlett, UT	09302000	Lake Powell	12
15	White River Near Watson, UT	09306500		
16	Green River At Green River, UT	09315000		

CRSS natural flow point	USGS Gage Name	USGS Gage #	Relevant 24MS/MTOM forecast sub-basin	Relevant MTOM/24MS forecast point
17	San Rafael River Near Green River, UT	09328500		
18	San Juan River Near Archuleta, NM	09355500	Vallecito Reservoir	10
			Navajo Reservoir	11
19	San Juan River Near Bluff, UT	09379500	Animas R. at Durango*	9*
			Lake Powell	12
20	Colorado R At Lees Ferry, AZ	09380000	Lake Powell	12
			Gains Powell to Lees Ferry Gage (not visible on map)	13
21	Paria River at Lees Ferry, AZ	09382000	Gains above Grand Canyon	14
22	Little Colorado River near Cameron, AZ	09402000		
23	Colorado River near Grand Canyon, AZ	09402500		
24	Virgin River at Littlefield, AZ	09415000	Gains above Hoover (Lake Mead)	15
25	Colorado River below Hoover Dam, AZ-NV	09421500		
26	Colorado River below Davis Dam, AZ-NV	09423000	Gains above Davis (Lake Mohave)	16
27	Bill Williams below Alamo Dam, AZ	09426000	Gains above Parker (Lake Havasu)	17
28	Colorado River below Parker Dam, AZ-CA	09427520		
29	Colorado River above Imperial Dam, AZ	09429490	Gains Parker to Imperial	18
NA	(CRSS only extends to Imperial)	--	Gains Imperial to Northerly International Border	19

Table 3.1 summarizes how water is aggregated in CRSS via natural flow points versus how it is aggregated in 24MS and MTOM via forecast points. The colors in the two right-most columns correspond to the colors of the MTOM/24MS sub-basins in Figure 3.1. In general, the table conveys spatial relationships and does not imply that natural flows are used directly to derive 24MS/MTOM forecasts (which are generated by the CBRFC). Forecast sub-basins/points with an asterisk (*) only exist in MTOM; the RiverWare rules used by MTOM need these sub-basins to approximate how

the reservoir operators use gage information when running the 24MS manually.

Inflows

Streamflow “forecasts” used in 24MS runs are actually flow sequences constructed by piecing together flows from some or all of the sources listed in Table 3.1.

ESP flow sequences are created by initializing the CBRFC models with current basin conditions (e.g., soil moisture, antecedent streamflow, snowpack). Then, historical 1981 to 2015 temperature and precipitation data are used to drive the CBRFC streamflow forecast modeling workflow, generating 35 equally likely 60-month forecasts from those initial conditions (Powell 2015). “Official” CBRFC forecasts combine near-term temperature and precipitation forecasts, ESP modeling, and expert forecaster analysis, the latter of which sometimes refines the forecast based on anticipated upcoming storms. The ESP and official forecasting procedures used by the CBRFC are described in more detail in Chapter 8.

24MS is run every month to generate “most probable” projections of reservoir levels. The inflow sequences used in these runs are constructed differently depending on the month. Figure 3.4 shows how construction of the Upper Basin most probable deterministic flow sequence varies over the course of a water year. To aid understanding of Figure 3.4, the October, January, and June sequences are described below.

In October, median flow values for the first three months are taken from the official forecasts provided by the CBRFC; for the rest of Year 1 (always defined as the span from the current month through the upcoming September), the monthly running median of the ESP forecast is used; Year 2 (always defined as the span from the upcoming October through following September) uses 30-year climatology *except* for October and November where a linear interpolation between the median ESP forecast value for September and climatology for January is used to smooth the sequence. This method uses actual forecasted values in the first three months only, it does not use or reflect actual forecasted values in the other months.

For January runs of the 24MS most probable run, flows for the first three months are again taken from median CBRFC official forecasts. April through July flow values are the median monthly values from the CBRFC’s April-through-July runoff forecasts. Starting with the August flow value, the flow sequences then revert to the same procedure used for the October flow sequences: median ESP through September followed by interpolation to climatology in Year 2 and beyond.

For the June most probable 24MS run, the first three months’ flows are median CBRFC official forecasts followed by median ESP values for September through Year 2.

	Year 1												Year 2												
Month Issued	Oct	Nov	Dec	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	
Oct	RFC	RFC	RFC	ESP Oct	ESP Oct	ESP Oct	ESP Oct	ESP Oct	ESP Oct	ESP Oct	ESP Oct	ESP Oct	interpolate	interpolate	30-yr Avg	30-yr Avg	30-yr Avg	30-yr Avg	30-yr Avg	30-yr Avg	30-yr Avg	30-yr Avg	30-yr Avg	30-yr Avg	
Nov		RFC	RFC	RFC	ESP Nov	ESP Nov	ESP Nov	ESP Nov	ESP Nov	ESP Nov	ESP Nov	ESP Nov	interpolate	interpolate	30-yr Avg	30-yr Avg	30-yr Avg	30-yr Avg	30-yr Avg	30-yr Avg	30-yr Avg	30-yr Avg	30-yr Avg	30-yr Avg	30-yr Avg
Dec			RFC	RFC	RFC	ESP Dec	ESP Dec	ESP Dec	ESP Dec	ESP Dec	ESP Dec	ESP Dec	interpolate	interpolate	30-yr Avg	30-yr Avg	30-yr Avg	30-yr Avg	30-yr Avg	30-yr Avg	30-yr Avg	30-yr Avg	30-yr Avg	30-yr Avg	30-yr Avg
Jan				RFC	RFC	RFC	Official A-J	Official A-J	Official A-J	Official A-J	ESP Jan	ESP Jan	interpolate	interpolate	30-yr Avg	30-yr Avg	30-yr Avg	30-yr Avg	30-yr Avg	30-yr Avg	30-yr Avg	30-yr Avg	30-yr Avg	30-yr Avg	30-yr Avg
Feb					RFC	RFC	RFC	Official A-J	Official A-J	Official A-J	ESP Feb	ESP Feb	interpolate	interpolate	30-yr Avg	30-yr Avg	30-yr Avg	30-yr Avg	30-yr Avg	30-yr Avg	30-yr Avg	30-yr Avg	30-yr Avg	30-yr Avg	30-yr Avg
Mar						RFC	RFC	RFC	Official A-J	Official A-J	ESP Mar	ESP Mar	interpolate	interpolate	30-yr Avg	30-yr Avg	30-yr Avg	30-yr Avg	30-yr Avg	30-yr Avg	30-yr Avg	30-yr Avg	30-yr Avg	30-yr Avg	30-yr Avg
Apr							RFC	RFC	RFC	Official A-J	ESP Apr	ESP Apr	interpolate	interpolate	30-yr Avg	30-yr Avg	30-yr Avg	30-yr Avg	30-yr Avg	30-yr Avg	30-yr Avg	30-yr Avg	30-yr Avg	30-yr Avg	30-yr Avg
May								RFC	RFC	RFC	ESP May	ESP May	interpolate	interpolate	30-yr Avg	30-yr Avg	30-yr Avg	30-yr Avg	30-yr Avg	30-yr Avg	30-yr Avg	30-yr Avg	30-yr Avg	30-yr Avg	30-yr Avg
Jun									RFC	RFC	RFC	ESP Jun	ESP Jun	ESP Jun	ESP Jun	ESP Jun	ESP Jun	ESP Jun	ESP Jun	ESP Jun	ESP Jun	ESP Jun	ESP Jun	ESP Jun	ESP Jun
Jul										RFC	RFC	RFC	ESP Jul	ESP Jul	ESP Jul	ESP Jul	ESP Jul	ESP Jul	ESP Jul	ESP Jul	ESP Jul	ESP Jul	ESP Jul	ESP Jul	ESP Jul
Aug											RFC	RFC	RFC	ESP Aug	ESP Aug	ESP Aug	ESP Aug	ESP Aug	ESP Aug	ESP Aug	ESP Aug	ESP Aug	ESP Aug	ESP Aug	ESP Aug
Sep												RFC	RFC	RFC	ESP Sep	ESP Sep	ESP Sep	ESP Sep	ESP Sep	ESP Sep	ESP Sep	ESP Sep	ESP Sep	ESP Sep	ESP Sep

RFC values are issued by the Colorado Basin River Forecast Center (RFC) as the official forecast values for the next three-month period of time. The values are calculated using Ensemble Streamflow Predictions (ESP) modeling and/or Statistical Water Supply (SWS) modeling.

Official A-J values are official forecast values issued by the RFC for the April-July runoff period using SWS and ESP. Apr-Jul water supply forecast volume is disaggregated by the RFC.

30-yr Avg values are the monthly average inflow values from the most recent 30 water years which is rolled forward every 10 years on the XXX1 year of each decade. For example, the 30-year average for 2014 would be 1981-2010. This data is calculated using a database maintained by the Bureau of Reclamation Upper Colorado Region (UCBOR). A water year begins October 1 and ends September 30.

Interpolated values are calculated by UCBOR and are based on percent of the 81-10 average. The method takes the percent of average of the previous month's forecast value and interpolates over two months to the percent of average for the month following the interpolation period. This is done to smoothly transition between the end of the current water year and the next water year.

ESP monthly values are generated using the RFC ESP forecasted volume for the water year using the current month's initial hydrological conditions. The RFC provides monthly volumes consistent with the 3-month forecast and the water year ESP volume.

Figure 3.4

24MS Most Probable Forecast construction methods for Upper Colorado unregulated inflows. (Source: Reclamation)

Lower Basin flow sequences for the most probable 24MS run are based on historical intervening flows. These are flows that have been calculated using mass balance between upstream and downstream gages. For each Lower Basin inflow, a trace is constructed by stringing together each month's 5-year average flow from the preceding five years. For example, the May inflow used in this run would be the average of the previous five May intervening flows and the June inflow would be the average of the previous five June intervening flows, etc. This is true for Years 1 and 2 and beyond.

In January, April, August, and October, two additional 24MS simulations are performed to characterize the uncertainty associated with the forecast; these are the "maximum probable" and "minimum probable." The flow sequences for these runs use the same data sources but in most places use

percentiles instead of averages. For the Upper Basin, the maximum probable traces are constructed using the 90th percentile of the CBRFC's official forecasts, April-through-July forecasts, and ESP forecasts in Year 1, then linear interpolation is used to match up with the 75th percentiles of monthly values from the 1981–2010 record. Year 3 (when modeled) reverts back to the 30-year average. The minimum probable traces are constructed the same way as the maximum probable traces except that they start with 10th percentile flows in Year 1, go to 25th percentile flows in Year 2, and then revert back to 30-year average flows. The percentiles used for maximum and minimum traces step back toward the mean because it is assumed that multiple years of extreme conditions in a row will not occur.

In January, April, and October, the maximum probable Lower Basin flows are constructed by stringing together flows corresponding to the 90th and 75th percentiles of the monthly flows from the preceding five years for Years 1 and 2, respectively, then reverting back to the average for Year 3 (i.e., the procedure for the most probable traces is used in Year 3). In a similar fashion, the 10th and 25th percentile flows are used to construct the flow sequence for the minimum probable trace. For August runs, the months of August and September use 5-year averages even for the maximum and minimum probable, and then Years 2 and 3 use 90th and 75th or 10th and 25th percentiles, respectively. Only the runs using the most probable flows are used for setting operational tiers.

Demands

Reclamation does not explicitly model Upper Basin water use in 24MS, but the unregulated inflow forecasts provided by the CBRFC have the impacts of some upstream uses in them (any “unmeasured” depletions and return flows are still represented in the inflows; the CBRFC’s unregulated streamflow development is discussed in more detail in Chapters 5 and 8). There are three exceptions: the 24MS model’s projections of monthly diversions from the Gunnison Tunnel, the Azotea Tunnel, and the Navajo Indian Irrigation Project (NIIP); the unregulated inflows provided by the CBRFC have not been depleted by those diversions. Lower Basin demands are modeled based on monthly schedules provided by water users. Water users provide updated schedules throughout the year.

Output

Output from 24MS consists primarily of monthly projected reservoir elevations, releases, and power generation. These results are posted in tabular form to the Reclamation website each month and provide decision support for basin stakeholders. Example 24MS output showing projected elevations in Lakes Powell and Mead from January, 2020 runs are provided in Figure 3.5 and Figure 3.6, respectively.

24MS output

Look for links under the heading “2-Year Projected Operations” at <https://www.usbr.gov/lc/riverops.html> for monthly tabulated 24MS output.

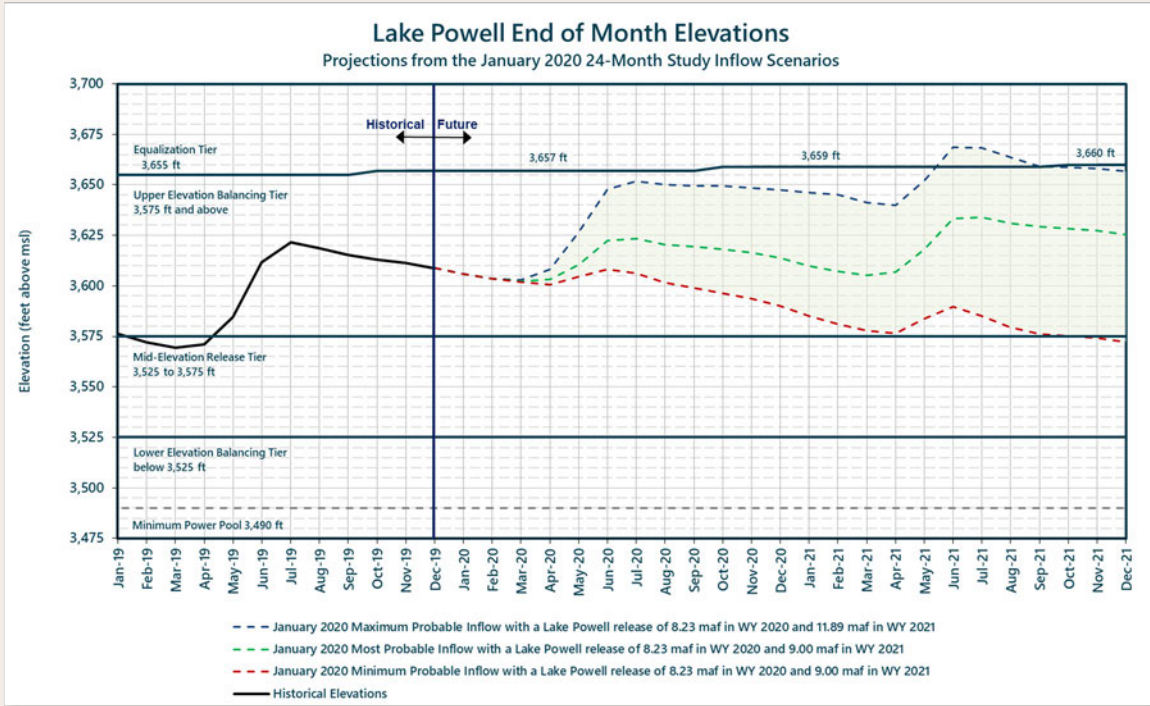


Figure 3.5

Example 24MS output for Lake Powell. (Source: Reclamation)

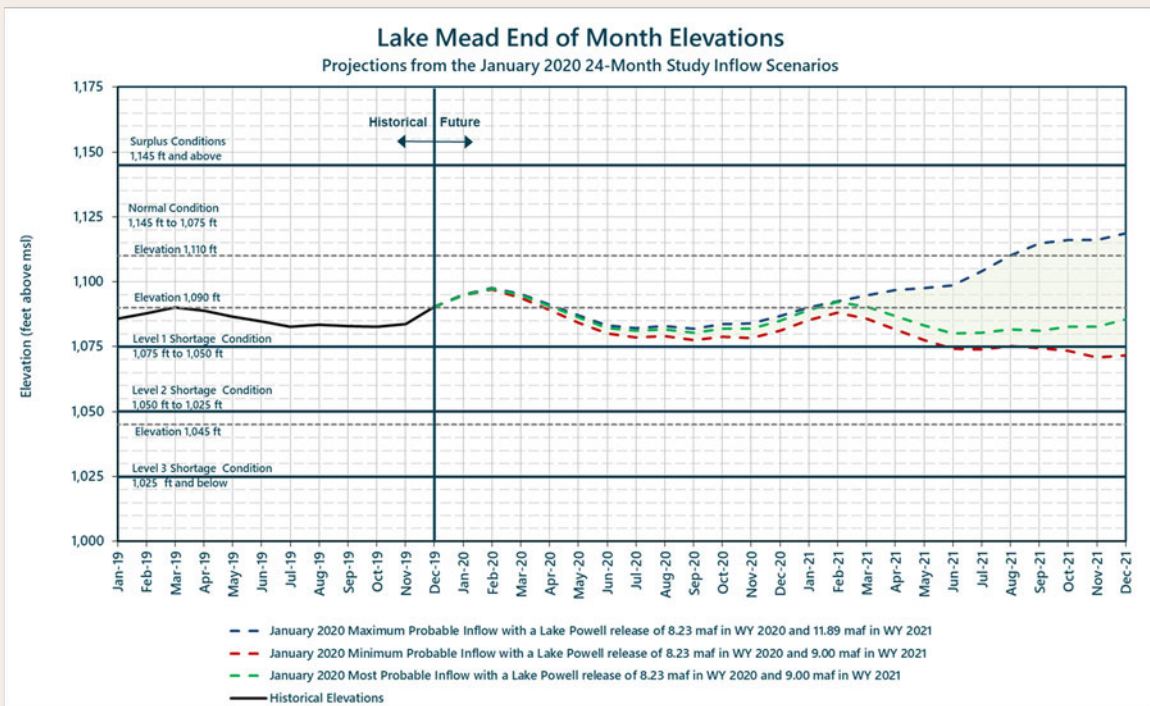


Figure 3.6

Example 24MS output for Lake Mead. (Source: Reclamation)

Mid-Term Probabilistic Operations Model (MTOM)

MTOM was developed in 2015 to enable Reclamation to simulate reservoir operations under a wider range of potential future streamflow than is used in 24MS (Bracken 2011; Reclamation 2015). The 24MS model is limited in its ability to incorporate hydrologic and operational uncertainty because it is a deterministic model that uses a single hydrologic trace and reservoir operations must be input manually. MTOM addresses this by using an ensemble of hydrologic traces and rules that execute reservoir operations throughout the basin in accordance with the Law of the River. The rules and their relationships are designed to mimic the process used to run the 24MS model (Reclamation 2015a). The current operational use of MTOM is to inform CRSS when generating 5-year projections (Reclamation provides the output of MTOM modeling upon request). Though the ability to use ensembles is advantageous for some purposes, MTOM cannot replace 24MS because current policy explicitly states that the most probable projections from 24MS will be used to set operations at Lakes Powell and Mead (U.S. Secretary of the Interior 2007; International Boundary and Water Commission 2017; Reclamation 2019c). Reclamation is currently working toward making MTOM projections more prominent and readily available.

Inflows

Like 24MS, MTOM runs are initialized with current reservoir conditions and the model takes unregulated streamflow forecasts as Upper Basin inflows. However, MTOM can use any number of hydrologic traces of 1 to 5 years in length instead of just one. MTOM's structure is almost identical to that of 24MS; it includes the same 12 reservoirs and inflow locations but has three additional forecast points in the Upper Basin: Yampa River at Deerlodge, Gunnison River gains between Crystal Reservoir and Grand Junction (including the North Fork of the Gunnison), and Animas River at Durango. These points were added to the model's structure and rule logic to automate a process that had been done manually in 24MS. Table 3.1 and the map in Figure 3.3 show these additional forecast points.

Demands

Water use and demands used in MTOM are also similar to those used in 24MS—only three Upper Basin diversions are projected in the model. However, the impacts of some use are represented in the unregulated flow forecasts provided by the CBRFC (see Chapters 5 and 8). Lower Basin demands are equal to the demand schedules provided by the Lower Basin states (Reclamation 2015a) in the current year of operations, and may be adjusted in the out years for different operating conditions.

MTOM is most commonly run using the 35 traces that make up the CBRFC's ESP forecasts but has more recently also been run with experimental forecasts (Baker 2019).

Output

MTOM output includes inflows, releases, reservoir contents, deliveries to water users, and indicators of operational conditions that are key to implementing the Interim Guidelines (Powell 2015). Currently, the most common use of MTOM is to initialize CRSS to produce 5-year projections of system conditions. See the “Development of five-year projections” section of this chapter for further information and an example of MTOM-CRSS output.

Colorado River Simulation System (CRSS)

Reclamation's first effort at computer simulation of the Colorado River system was in 1969, as part of studies to support the Long Range Operating Criteria negotiations (Reclamation 1969). That work was followed by Reclamation's development of the Colorado River Simulation Model in the 1970s, written in FORTRAN. A database of model inflows and demands was developed in the 1980s and the combined modeling tool—basin model plus database plus output utility—was called the Colorado River Simulation System, or CRSS (Reclamation 1983). CRSS was implemented in RiverWare in 1996 with essentially the same spatial and temporal resolution as the original FORTRAN model (Reclamation 2010). Over the years, features have been added to CRSS that have improved its user interface, analysis capabilities, database management system, and output summarization capabilities. CRSS is also updated to represent new or refined information about the system, e.g., physical relationships and new operational policies. Note that water salinity is also simulated in CRSS, but that capability is not discussed in this report.

CRSS enables Reclamation to explore impacts to the basin under different supply, demand, and policy configurations for years to decades into the future. It has been used for policy analyses in dozens of studies, including the Interim Guidelines EIS (Reclamation 2007f), the Basin Study (Reclamation 2012e), Minutes 319 and 323 (International Boundary and Water Commission 2012; 2017), and the Colorado River Basin Ten Tribes Partnership Tribal Water Study (Reclamation 2018). Most recently, it was used to provide guidance for basin-wide drought contingency planning (Reclamation 2019c). CRSS is currently being used in studies of how climate change hydrology derived from the Coupled Model Intercomparison Project Phase 5 (CMIP5) affects future projections (Chapter 11). It is also currently used in conjunction with 24MS or MTOM, or both, to generate official 5-year projections.

The Upper Basin reservoirs in CRSS are slightly different from those represented in 24MS and MTOM: Fontenelle, Flaming Gorge, Starvation (which is a lumped representation of multiple smaller reservoirs), Taylor Park, Blue Mesa, Morrow Point, Crystal, Navajo, and Powell (Vallecito is only in 24MS and MTOM while Starvation is only in CRSS). The Lower Basin reservoirs are the same: Mead, Mohave, and Havasu.

CRSS simulations always start in January. When running the model in any month other than January it is initialized using projections from the 24MS or MTOM of December 31 of the current year, and the CRSS simulations start in January of the following year. Reservoir operations are simulated via rulesets reflecting either current Law of the River or potential future alterations to operations.

Inflows

Of the 29 inflow points in CRSS, 14 are upstream of Reclamation's headwaters reservoirs and 15 are intervening flows along reaches within the model (Reclamation 2007a). The map in Figure 3.7 shows the inflow points represented in CRSS. The inflow points on the map correspond to the USGS gages listed in Table 3.1. Table 3.1 also describes the relationships between CRSS inflow points and the forecast points used in 24MS and MTOM.

Unlike the inflows to 24MS and MTOM, which are based on unregulated inflow forecasts from the CBRFC, CRSS uses natural flow as streamflow inputs. The terms "unregulated" and "natural" describe the level of upstream human activity remaining in the inflow datasets after naturalization calculations are made. The CBRFC unregulated inflows, described in detail in Chapters 5 and 8, are forecasted streamflows that are adjusted for upstream measured diversions, imports, and reservoir regulation. They do not account for upstream unmeasured uses or unmeasured return flows. In contrast, in the CRSS natural flow dataset, observed streamflows are naturalized by backing out both measured and unmeasured impacts, including consumptive uses, imports, and reservoir operations (see Chapter 5 for details about naturalization).

The CRSS streamflow paradigm allows Reclamation to simulate reservoir operations under long-term projections of both supply and demand. Hundreds of historical and theoretical inflow time-series or traces have been analyzed in CRSS to evaluate system impacts under different hydrologic assumptions. These assumptions generally fall into three categories: observed hydrology, paleohydrology, and climate change-informed hydrology. Development and use of data in each of these categories is described in detail in Chapters 5, 9, 10, and 11 of this report.

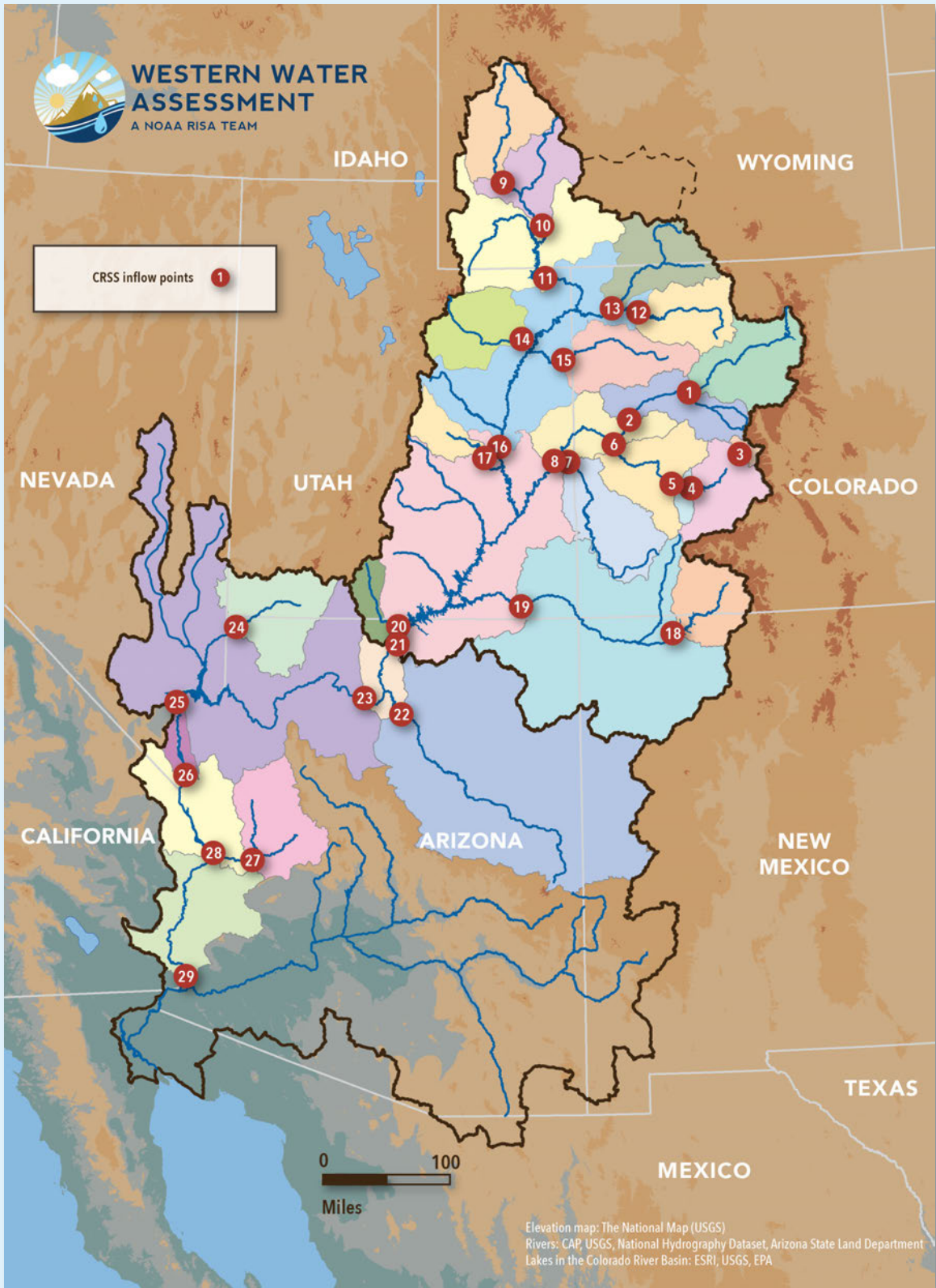


Figure 3.7
Map of CRSS inflow points. See Table 3.1 for details about each inflow location. (Source: Reclamation)

Demands

The 115 delivery points in CRSS represent about 500 water users throughout the basin across all sectors. In the Lower Basin, each mainstem user is individually represented. In the Upper Basin, nodes often represent spatial aggregations of many water users. To understand representation of water use in CRSS it is necessary to distinguish between demand (volume of water needed to meet identified uses), diversion (volume of water withdrawn from the river system), and depletion (volume of water that is diverted and not returned to the river after use). In the Upper Basin, long-term demand projections that increase over time are provided to Reclamation by the Upper Colorado River Commission (UCRC). The official projections currently used were developed in 2007. These demands are modeled in CRSS via diversion and depletion schedules provided by the states (Reclamation 2007d). The Upper Basin states produced [updated depletion schedules in 2016](#) for eventual incorporation into Reclamation models (see callout box; S. McGettigan, pers. comm.). In exploratory studies, a variety of future demand scenarios are tested in CRSS to understand system response to climatic and social impacts on demands (Reclamation 2012b).

In CRSS, when there is not enough water, users in the Upper Basin experience shortage. Because CRSS does not model water allocation based on water rights, the Upper Basin shortages occur to the aggregated demands, irrespective of seniority, and therefore are not reported as shortages to individual demands.

For the Lower Basin states and Mexico, there are multiple diversion and depletion schedules that allow CRSS to model water use under surplus conditions, normal conditions, and the prescribed reductions under specific shortage conditions. Per the Interim Guidelines (U.S. Secretary of the Interior 2007), all Powell and Mead operating conditions are determined based on August projections of January 1 elevations. For long-term studies, CRSS does not replicate an August projection, it sets the upcoming year's operating conditions using its "actual" modeled January 1 reservoir contents. Additionally, the Lower Basin states and Mexico provide Intentionally Created Surplus (ICS) and Intentionally Created Mexican Allocation (ICMA) schedules and assumptions, respectively, that may increase or decrease deliveries in any given year.

Output

Typical CRSS simulations yield time series of reservoir releases, water surface elevations, hydropower generation, consumptive uses, and streamflows at select locations. The results of ensembles of runs are often summarized statistically to give a sense of the distribution of potential future conditions, as shown in Figure 3.8.

Updated depletion schedules from UCRC

The currently used Upper Basin depletion schedule, dated December, 2007, is available here:

http://www.ucrc.com/RepDoc/DepSchedules/DepSchedules_2007.pdf

And an updated depletion schedule, dated December, 2016, is available here:

<http://www.ucrc.com/RepDoc/DepSchedules/CurFutureDemandSchedule.pdf>

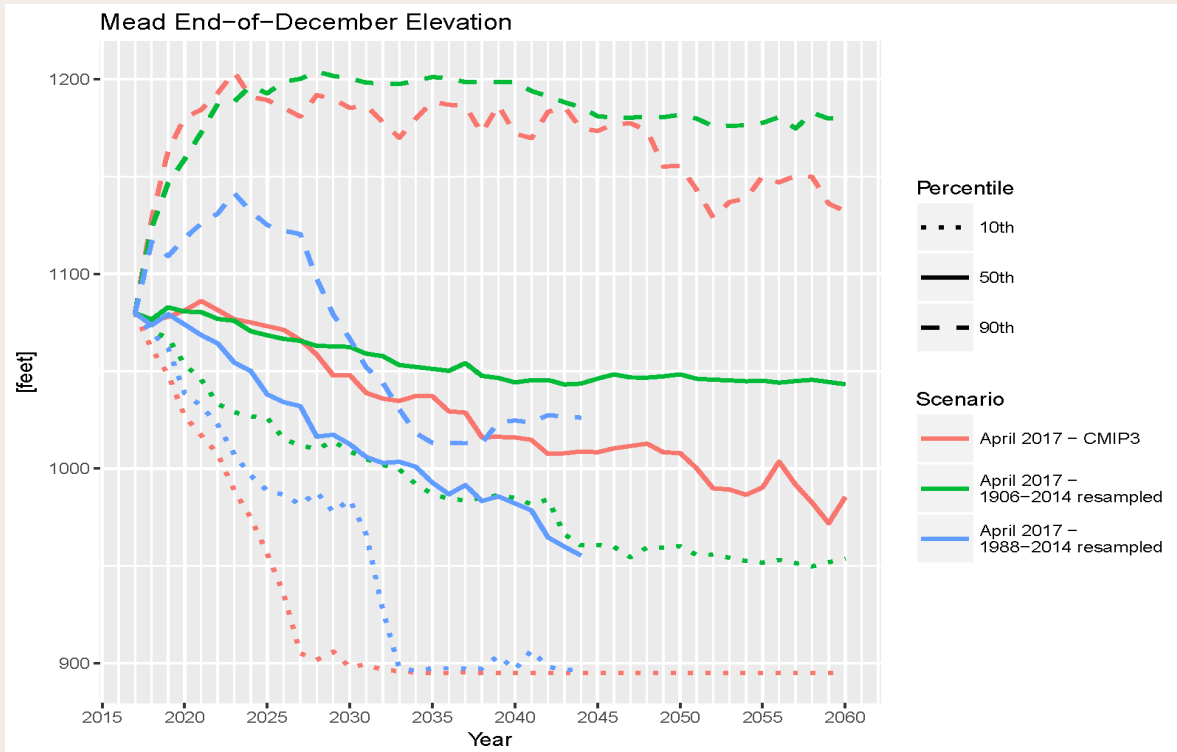


Figure 3.8

Example CRSS results. (Reclamation 2018)

Development of Five-Year Projections

For studies that look beyond Year 1, 24MS or MTOM is combined with CRSS to take advantage of the capabilities of all three models. A key example of this is the generation of official 5-year projections. The combined modeling approach for those studies is shown in Figure 3.9.

Because MTOM has demonstrated skill at 1- to 2-year lead times (Baker 2019), Reclamation uses it, with ESP forecasts, to simulate the first year, yielding 35 projections of end-of-year reservoir elevations. Those projections are then used to initialize CRSS. Each initialized CRSS run uses multiple, long-term naturalized flow traces generated by the index sequential method. (The index sequential method, or ISM, is described in Chapter 9.) Besides its demonstrated skill, an additional advantage to simulating the first year in MTOM is that it incorporates uncertainty during that year that, when combined with the ISM traces, represents a broader range of potential future conditions.

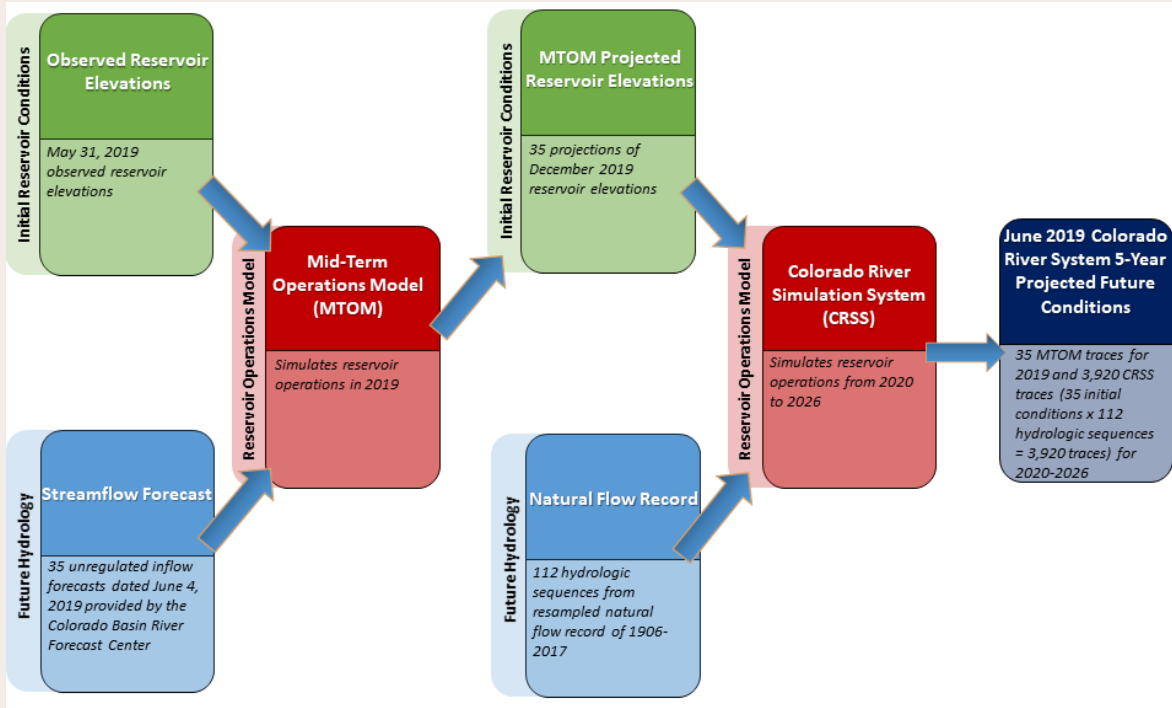


Figure 3.9

Schematic showing how MTOM and CRSS can be coupled to perform five-year projections. December 31 projections from 24MS are used instead of MTOM projections toward the end of the calendar year when there is little uncertainty. (Source: Reclamation website page "[Colorado River System 5-Year Projected Future Conditions](https://www.usbr.gov/lc/region/g4000/riverops/crss-5year-projections.html), <https://www.usbr.gov/lc/region/g4000/riverops/crss-5year-projections.html>, 2019)

Example output from combined MTOM-CRSS runs made in August, 2019 is provided in Figure 3.10 below. In this example, 35 unregulated inflow forecast traces from the CBRFC were used in MTOM to simulate 35 sets of potential December 31, 2019 reservoir elevations. These 35 sets provided a distribution of potential December 31, 2019 reservoir elevations and became the initial reservoir conditions used in CRSS, with ISM sequences, to simulate years 2020 through 2024. This modeling workflow generates a distribution of different operational conditions through 2024.

Percent of Traces with Event or System Condition. Results from August 2019 CRSS (Updated December 2019) using the Full Hydrology (resampling of the full natural flow record 1906-2017).

Event or System Condition	2020	2021	2022	2023	2024
Upper Basin - Lake Powell					
Equalization Tier (Powell >= Equalization [EQ] Elevation)	13	26	24	30	27
Equalization - annual release > 8.23 maf	13	26	24	29	26
Equalization - annual release = 8.23 maf	0	0	0	<1	<1
Upper Elevation Balancing Tier (Powell < EQ Elevation and >= 3,575 ft)	87	72	59	53	55
Upper Elevation Balancing - annual release > 8.23 maf	3	39	35	34	32
Upper Elevation Balancing - annual release = 8.23 maf	84	33	24	18	23
Upper Elevation Balancing - annual release < 8.23 maf	0	0	0	<1	0
Mid-Elevation Release Tier (Powell < 3,575 and >= 3,525 ft)	0	2	17	16	16
Mid-Elevation Release - annual release = 8.23 maf	0	0	0	0	2
Mid-Elevation Release - annual release = 7.48 maf	0	2	17	16	14
Lower Elevation Balancing Tier (Powell < 3,525 ft)	0	0	0	<1	2
Below Minimum Power Pool (Powell < 3,490 ft)	0	0	0	0	0
Lower Basin - Lake Mead					
Surplus Condition - any amount (Mead >= 1,145 ft)	0	0	7	12	19
Surplus - Flood Control	0	0	<1	3	3
Normal Year or ICS Surplus Condition (Mead < 1,145 and > 1,075 ft)	100	96	69	54	45
Recovery of DCP ICS / Mexico's Water Savings (Mead >=>= 1,110 ft)	0	9	19	27	32
DCP Contribution / Mexico's Water Savings (Mead <= 1,090 and > 1,075 ft)	100	70	44	31	25
Shortage Condition - any amount (Mead <= 1,075 ft)	0	4	24	33	37
Shortage / Reduction - 1st Level (Mead <= 1,075 and >= 1,050 ft)	0	4	24	26	23
DCP Contribution / Mexico's Water Savings (Mead <= 1,075 and >= 1,050 ft)	0	4	24	26	23
Shortage / Reduction - 2nd Level (Mead < 1,050 and >= 1,025 ft)	0	0	0	7	11
DCP Contribution / Mexico's Water Savings (Mead < 1,050 and > 1,045 ft)	0	0	0	3	6
DCP Contribution / Mexico's Water Savings (Mead <= 1,045 and > 1,040 ft)	0	0	0	2	<1
DCP Contribution / Mexico's Water Savings (Mead <= 1,040 and > 1,035 ft)	0	0	0	<1	2
DCP Contribution / Mexico's Water Savings (Mead <= 1,035 and > 1,030 ft)	0	0	0	2	<1
DCP Contribution / Mexico's Water Savings (Mead <= 1,030 and >= 1,025 ft)	0	0	0	0	<1
Shortage / Reduction - 3rd Level (Mead < 1,025 ft)	0	0	0	0	3
DCP Contribution / Mexico's Water Savings (Mead <=<= 1,025 ft)	0	0	0	0	3

Figure 3.10

MTOM-CRSS output example. The figure shows the percent of traces with event or system condition. Results from August 2019 MTOM/CRSS using the full natural flow record. (1906–2017) (Source: Reclamation webpage “[Colorado River System 5-Year Projected Future Conditions](https://www.usbr.gov/lc/region/g4000/riverops/crss-5year-projections.html)” <https://www.usbr.gov/lc/region/g4000/riverops/crss-5year-projections.html>)

3.3 Uncertainty and error

The purpose of Reclamation modeling is to project future system conditions given varying inputs and operations. In the short-term, e.g., when running 24MS, the inputs are forecasts that incorporate *some* skillful knowledge of upcoming hydrology, water use, etc. For mid- and long-term modeling, inputs are based on ranges of *possible* futures. Any projection of the future is inherently uncertain, but uncertainty increases as projections go further out. Simplifications and assumptions required to model the system also introduce uncertainty into projections. Since both the input data and the representation of the system are imperfect, there are uncertainties at each step. Though each of the Reclamation models handles uncertainty differently, they are all impacted by four primary sources: streamflow, initial conditions, water use and demand, and reservoir operations.

Streamflow

Of the four sources, uncertainty in future streamflow has the largest impact on system projections. The three Reclamation models take inflows that have been developed through multiple methods applied to many different data types. Each inflow dataset has a provenance that reflects the availability of primary data, intermediate analytical techniques and models, and the goals of the application of the dataset. The inflow datasets are discussed in detail in Chapters 5, 8, 9, 10, and 11.

24MS and MTOM both currently use unregulated streamflow generated by the CBRFC. The observations, historical relationships, and assumptions built into their forecasting framework all aggregate into the streamflow Reclamation uses in its models. Reclamation contributes additional uncertainty to streamflow inputs to 24MS and MTOM by, for example, using historical averages for Lower Basin flows, calculating intervening flow through a mass balance calculation, and interpolating between CBRFC products. For studies using 24MS, uncertainty is acknowledged four times per year by simulating probable minimum and maximum hydrology (in January, April, August, and October). Annual Year 1 streamflow uncertainty decreases throughout the year as snowpack and temperature conditions develop. The case is the same with MTOM, although it is always run with ensemble hydrology and results are presented as probabilistic views of a range of possible outcomes rather than as a single outcome.

Historical natural flow used in CRSS has different sources of uncertainty than unregulated flow. It is a purely derived product; Reclamation uses data collected from USGS and other operators' gage sites, consumptive use records, records of reservoir storage and releases, and other data to compute the natural flow. Simplifications in all of these data sources propagate through the computation. Intervening natural flows have additional uncertainty because they are calculated via mass balance

between measured flows and become catchalls for residual errors in groundwater interactions and non-natural components of the upstream inflows, such as reservoir evaporation and bank storage, rather than reflecting natural gains and losses exclusively. Reclamation is aware of these issues; their work plan includes additions or refinements to estimates of Upper Basin irrigated acreage and evapotranspiration, Lower Basin consumptive use, and both Lake Powell and Lake Mead evaporation.

Although the historical natural flow uncertainties described above do exist, CRSS is also often driven by synthetic hydrologic inputs that attempt to capture long-term changes. To the extent that the synthetic hydrology is independent of the natural flows, uncertainties in generating natural flows become less relevant, though synthetic flows also carry some level of uncertainty depending on how they were developed.

Initial conditions

24MS and MTOM are always initiated with current reservoir conditions so initial conditions are not a source of uncertainty for these models. CRSS is initialized with December 31 projections of the current year from either 24MS or MTOM. Specifically, for the August CRSS run only one set of initial conditions from the 24MS model are used because there is little uncertainty in the end-of-calendar-year reservoir elevations and because the coordinated reservoir operations for the upcoming year are determined by that 24MS run. In any other month, the CRSS initial conditions are taken from a set of 35 MTOM projections. This uncertainty is intentional and enables Reclamation to present a broader range of potential future conditions.

Water use and demand

In 24MS and MTOM, the only representations of Upper Basin water use are the implicit unmeasured depletions and return flows left in CBRFC's unregulated flow forecasts and the three diversions described in previous sections. As such, the uncertainty about water use is a function of Upper Basin unmeasured depletions and return flows and Reclamation's or water users' projections of the three diversions. In the Lower Basin, water users provide monthly water use schedules. The uncertainty in Year 1 Lower Basin water use can be significant early in the year but decreases as the year progresses. Sources of water use and demand uncertainty are similar in MTOM, but most projections are based on historical schedules and embedded model logic so the uncertainty does not decrease over time.

Water demand assumptions for CRSS are provided by the Upper and Lower Basin states and key water users throughout the basin. Significant uncertainty exists when projecting future demand, but this uncertainty is greater in the Upper Basin than in the Lower Basin because Lower Basin water users have reached their full apportionments. Incomplete records of

historical demand in the Upper Basin (as opposed to consumptive use, which is computed) further confound this issue because it is difficult to know how much projected demand deviates from historical demand. To address this uncertainty, the 2012 Basin Study (Reclamation 2012e) adopted a scenario planning approach to project future basin-wide water demand. The application of such an approach represents a new paradigm in the basin and a significant advancement in basin long-term planning. Reclamation and the basin states recognize the importance of continued refinement of scenario planning as part of a robust long-term planning framework for the basin.

Reservoir operations

Reclamation's models must represent complex operating policies, some of which are at sub-monthly timescales, through rules, which introduce uncertainty into projections. Some sources of uncertainty can be reduced with sufficient information and some cannot (e.g., adaptive management provisions for reservoirs or futures where no operational detail is provided). Reclamation has begun using hindcasts to identify sources of uncertainty that can be addressed. Hindcasts are performed by initializing a model to a historical state and using perfect knowledge of "future" conditions as inputs. This allows Reclamation to differentiate model uncertainty from input uncertainty.

Current estimates of projection uncertainty

One approach to understanding uncertainty in Reclamation projections is to compare the results of 24MS most probable runs to what actually occurred. This is the equivalent of quantifying error in the projections due to all uncertainties combined. Figure 3.11 shows the evolution of error in reservoir elevation projections for 24MS runs performed each month for the years 2008 to 2014 (Reclamation 2019b). The outlook length is longest on the left hand side of the plot (i.e., the January projection of the December 31st elevation 24 months in the future) and the lead time decreases going toward the right hand side of the plot. Error is highest at longer lead times and decreases over the course of the monthly projections. The projected year, e.g., 2013, is used as the symbol indicating how accurate each projection of that year was from 24 months in advance to the simulation performed in December 2013. For example, because 2013 was a dry year, the projection of Lake Powell's elevation 24 months in advance (i.e., the projection made in January 2011) was far higher than the eventual elevation.

In general, 24MS projections are more accurate at shorter lead times, though there are exceptions. The largest errors occurred in extreme years: 2011 was very wet while 2012 and 2013 were very dry. The year 2011 also demonstrates how, when the forecasted Lake Powell inflow results in a change of projected operating tiers, there can be significant implications

for the skill of Lake Mead projections. August end of calendar year projections, highlighted in green, averaged less than 2 feet of error for the 2008 to 2014 period.

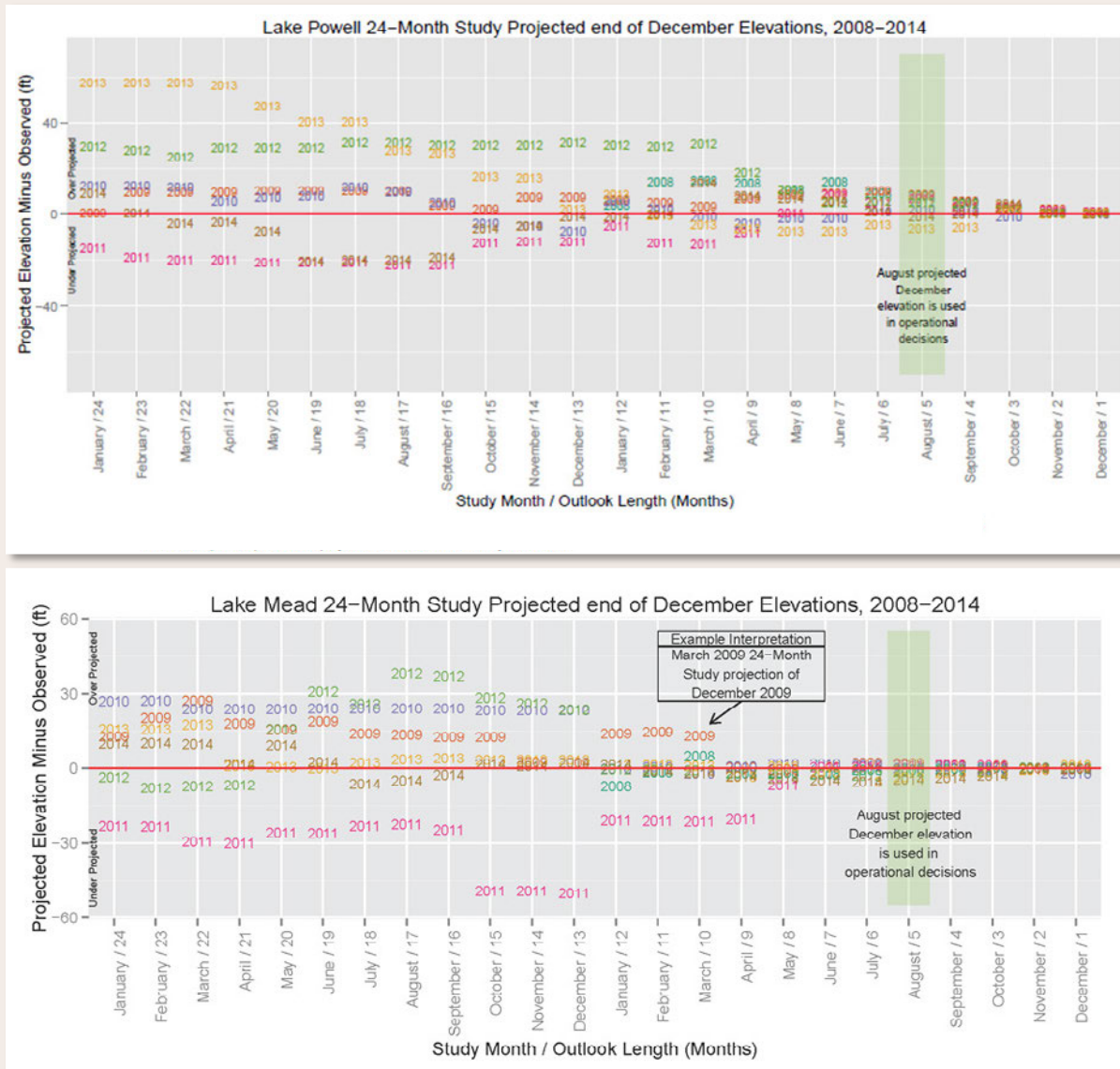


Figure 3.11

Projections of Lakes Powell and Mead EOY elevation compared with observed values from various outlook lengths (each point represents a projection of December of the year shown) for the period 2008–2014. (Source: Reclamation 2019b).

It is important to understand these errors and reduce uncertainty where possible because of the decision-making context of 24MS. Reservoir projections used in tier determinations can be sensitive to fairly small errors in inputs to 24MS, particularly when Lake Powell or Lake Mead elevations are hovering near tier thresholds. For example, 24MS currently uses 5-year running average values for intervening flows between Lake Powell and Lake Mead. Observed intervening flows can deviate from those averages enough to change Mead's elevation by a few feet, potentially moving it from normal to shortage operations or vice versa (FROMUS; Reclamation and Colorado Basin River Forecast Center in preparation).

As discussed above, the importance of the uncertainty underlying MTOM and CRSS projections is conceptually different from how it impacts 24MS because they were developed to assess risk under uncertainty. Additionally, CRSS is often used to compare risks under different future supply, demand, or operations scenarios, i.e., it is used to evaluate the sensitivity of the system to different inputs or assumptions (Reclamation 2012e).

Ongoing efforts to address uncertainty

In addition to the efforts mentioned under specific headings above, Reclamation is engaged in multiple projects to identify, reduce, or account for uncertainty in each of the three models. In collaboration with the CBRFC, Reclamation is preparing a report identifying the sources of error and uncertainty associated with 24MS. The draft Forecast and Reservoir Operation Modeling Uncertainty Scoping report (Reclamation and Colorado Basin River Forecast Center in preparation) addresses over a dozen parameters, summarizes the cost and time required to reduce the error and uncertainty in each of them, and estimates the impact that reduction would have on 24MS projections.

A version of MTOM was adapted to be run in “verification mode” to produce hindcasts as part of recently completed research that uses MTOM as a testbed for experimental hydrology forecasts (Baker 2019). Results of the hindcasting are currently being drafted in a Reclamation report. MTOM will continue to be refined as further studies are completed.

A CRSS verification model has also been developed, but hindcast studies are in preliminary phases. Finally, because long-term hydrologic uncertainty is extremely large and cannot be reduced, Reclamation continues to explore decision-making under deep uncertainty (DMDU) methods similar to the robustness concepts used during the 2012 Basin Study (Reclamation 2012e).

3.4 Limitations due to simplification

All models of river basin systems have limitations because they are simplifications, in both space and time, of complex physical and institutional processes. Simplification is clearly reasonable but it can introduce error that affects the ability of Reclamation and others to accurately simulate the Colorado River Basin and limits the level of analysis that can be performed.

Representation of natural flows in the Upper Basin

Natural flows in the Upper Basin are represented by aggregating large runoff-producing areas on the Colorado, Green, and San Juan rivers. This level of spatial resolution was set with the original FORTRAN model built in the 1980s (Reclamation 1983) and has changed very little (the current version contains an additional inflow point on the Taylor River). Wheeler, Rosenberg, and Schmidt (2019) describe in detail the implications of both the spatial and temporal resolution on the utility of CRSS for particular types of analyses in the Upper Basin. They assert that the coarse resolution of CRSS in the Upper Basin is “inappropriate for use in resolving water supply and environmental tradeoffs in many tributary watersheds such as the upper Colorado, Dolores, Yampa, Little Snake, Duchesne, White, San Rafael, Little Colorado, or Virgin River watersheds” (Wheeler, Rosenberg, and Schmidt 2019). It is also true, however, that CRSS was not designed to perform those types of analyses and was rather designed as a tool for long-range basin planning centered on the federal reservoirs. The impacts of CRSS’s coarse resolution in the Upper Basin on scenario outcomes have not been studied.

The development and limitations of natural flows are discussed in further detail in Chapter 5.

Representation of natural flows in the Lower Basin

The treatment of Lower Basin tributaries in CRSS limits the ability to fully assess the natural water supply of the basin (Reclamation 2012e). For four of the inflow points below Lees Ferry (the Paria, Little Colorado, Virgin, and Bill Williams rivers), CRSS uses historical inflows (not natural flows) based on USGS streamflow gages. In addition, the Gila River is not included in CRSS, making the uncertainties associated with the Gila River and the other Lower Basin tributaries and how they may contribute to system reliability difficult to discern (Lukas, Wade, and Rajagopalan 2013).

Since the 2012 Basin Study, Reclamation has been engaged in efforts to 1) resolve and correct, in collaboration with the basin states, the methodological and data inconsistencies in Reclamation’s Consumptive Uses and Losses Reports pertaining to all of the Lower Basin tributaries (Reclamation “Plans & Reports” n.d.); 2) develop natural flows for the Little Colorado, Virgin and Bill Williams rivers and modify CRSS to use natural

flows for those tributaries; and 3) explore the feasibility and usefulness of computing natural flows for the Gila River Basin and the feasibility and usefulness of adding that basin to CRSS. See Basin Study supplements Appendix C11 and Tech Report C (Reclamation 2012a; 2012d) for more-detailed discussions of these issues.

Representation of the physical and institutional setting

The spatial and temporal detail of CRSS (and 24MS and MTOM) limit the ability to assess impacts to basin resources, in particular water deliveries and shortages in the Upper Basin and ecological resources (Reclamation 2012e). For example, over 4,000 square miles of watershed above Glenwood Springs are simplified, lumping headwater reservoir operations, major exports to the Front Range, and over 100,000 acres of irrigated agriculture at one node. Limitations due to the spatial simplifications of CRSS are also described by Wheeler, Rosenberg, and Schmidt (2019). Such simplifications require that natural systems are evaluated through approximations at larger spatial scales and longer time steps (e.g., monthly versus daily) than preferred or required for more detailed assessments.

Simplifications in CRSS's institutional representation of the basin also result in limitations. For example, CRSS tracks shortages in the Upper Basin when the flow is insufficient to meet the local demands as opposed to simulating the complex water rights system in each state that would be needed to appropriately model shortages to individual water rights holders. In addition, CRSS does not have the capability to assign Upper Basin shortages in the event that a "Compact Call" is modeled; in such cases CRSS injects deficit water directly above Lake Powell.

The implications of this limitation were made clear in the 2012 Basin Study and in the 2018 Ten Tribes Partnership Study. During the 2012 Basin Study analyses, it was discovered that two senior downstream water rights in Colorado were subject to shortages in the model despite their priority, because CRSS allocates water sequentially from upstream to downstream. This issue was identified and rectified by modifying CRSS to ensure that these two particular senior rights (the Shoshone Power Plant and the senior users from the Grand Valley Irrigation Company) were satisfied before upstream rights received water (Reclamation 2012f). In the 2018 Ten Tribes Partnership Study, to partially address the water rights concern, the CRSS representation of a tribal diversion on the Duchesne River was moved upstream to ensure that it received its senior allocation, and the State of Colorado's StateMod model was used for simulation of tribal rights on the San Juan River in order to ensure the proper allocation to water rights in that basin (Reclamation 2018).

The general areas of uncertainty, error, and limitations noted above begin with the input data and extend through the representation of the

institutional setting. As noted, in most cases, the areas present opportunities for additional research and development and improvement of model representation and available data. Reclamation continues to pursue these opportunities, as appropriate, in an effort to continually improve their modeling capabilities.

3.5 Challenges and opportunities

Challenge

Each Reclamation model (24MS, MTOM, and CRSS) has different ways that uncertainty can be better quantified and either addressed or incorporated. In particular, each model uses a more simplistic method for projecting future inflows in the Lower Basin than in the Upper Basin (5-year averages for 24MS and MTOM rather than a forecast, and gaged flow in CRSS rather than natural flow). In the Upper Basin, demand projections may differ from actual water use trends and the representation of complex operating policies via rules deployed at the monthly time step may further contribute to this deviation. Finally, more in-depth analyses are needed to verify how well modeled operational policies reflect actual operations. (Challenges associated with hydrologic uncertainty are described in Chapters 5, 8, 9, 10, and 11.)

Opportunities

- Complete FROMUS report and update its findings as models are refined.
- Work with the CBRFC to develop unregulated flow forecasts for the Lower Basin.
- Continue to work toward commitments outlined in the Colorado River Basin Study regarding the development of natural flows in the Lower Basin.
- Work with Upper Basin states, water users, and tribes to refine long-term demand projections.
- Complete hindcasting studies that can help identify how simplifications in Reclamation's models contribute to projection error.

Challenge

The coarse spatial resolution in CRSS has implications for studying demands and tributary flows. In the Upper Basin, water demands are represented in highly aggregated nodes and do not reflect water right priorities, which limits the ability to accurately model shortages to specific users under different scenarios. On the Lower Basin tributaries, because gaged flow is used rather than natural flow, demands are not explicitly modeled. CRSS uses a monthly time step that limits the ability to analyze the impacts to certain resources, in particular, ecological resources. Additionally, the exclusion of smaller tributaries limits the analyses that can be performed with CRSS.

Opportunities

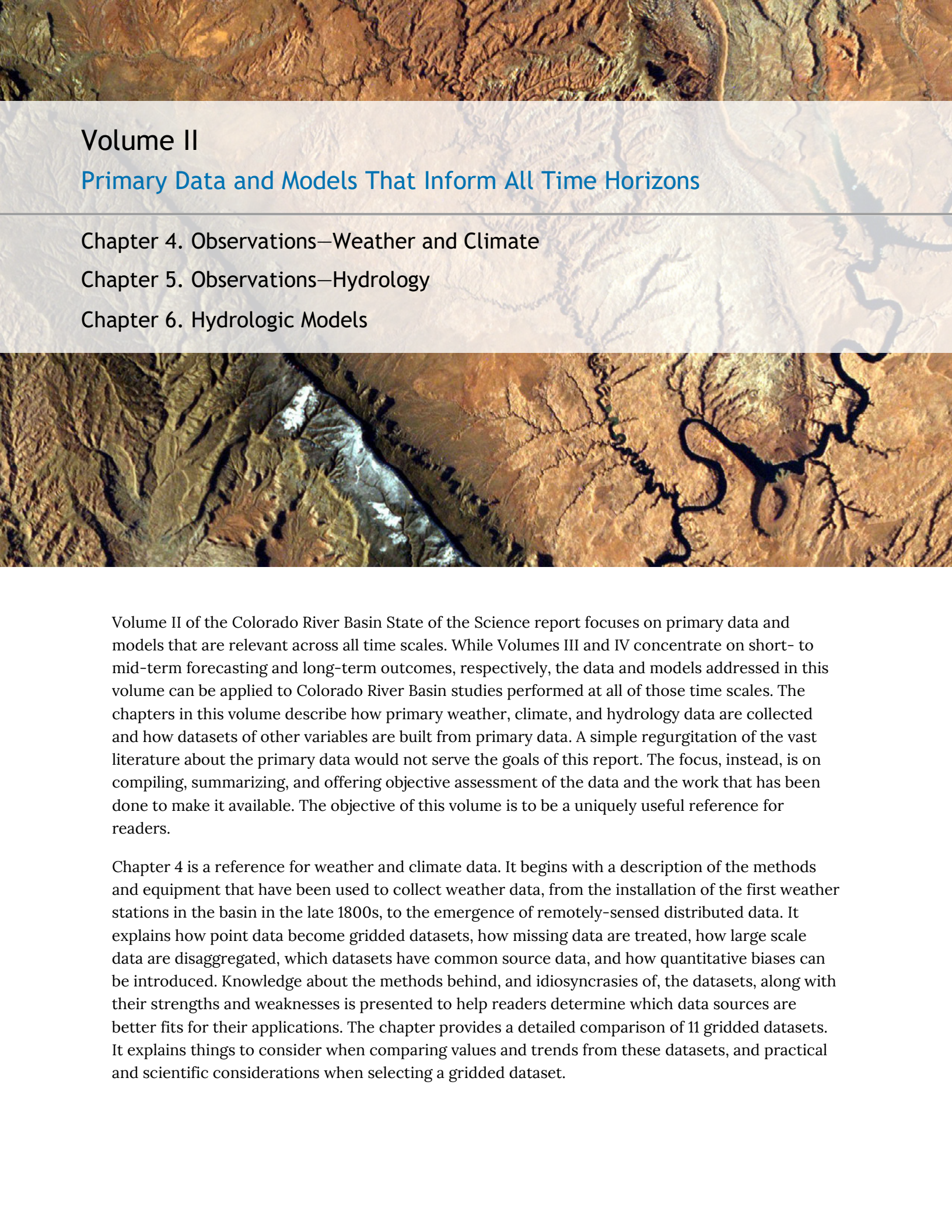
- Review the configuration, number of nodes, and rules in the Upper Basin to explore implementing an allocation system that captures the distribution of water supply by water rights priority.
- The quality, coverage, and resolution of data that is used to naturalize inflows has improved and might support model disaggregation in both time and space.
- Explore iterative sub-basin implementations that are solved at shorter time scales or finer resolutions and that may be aggregated and fed into existing nodes in CRSS.

Challenge

Reclamation models are complex and the projections they generate are the product of combinations of many data sources and assumptions. It is critical that stakeholders and the public understand the uncertainty and how this uncertainty affects projections of risk in order to ensure the appropriate use of the results for decision making. Reclamation continues to work toward improving such communication but there is room for improvement. Additionally, the models are not comprehensively documented, despite their critical importance in Colorado River Basin management and planning.

Opportunities

- Continue to improve and refine communication of model assumptions and uncertainty on Reclamation's modeling website and in widely distributed modeling results (e.g., the 24MS reports).
- Develop comprehensive, technical overviews of each of the models to share how each model is configured, how the rules are implemented, and how the inputs are derived.

The background of the page is an aerial photograph of a rugged, mountainous landscape. The terrain is characterized by deep, winding river valleys and steep, rocky slopes. The colors range from light tan and beige to dark brown and black, indicating different geological and hydrological features. A prominent river valley runs diagonally across the center of the image, with a winding river visible in the lower right quadrant. The overall scene is one of a complex, high-altitude environment.

Volume II

Primary Data and Models That Inform All Time Horizons

Chapter 4. Observations—Weather and Climate

Chapter 5. Observations—Hydrology

Chapter 6. Hydrologic Models

Volume II of the Colorado River Basin State of the Science report focuses on primary data and models that are relevant across all time scales. While Volumes III and IV concentrate on short- to mid-term forecasting and long-term outcomes, respectively, the data and models addressed in this volume can be applied to Colorado River Basin studies performed at all of those time scales. The chapters in this volume describe how primary weather, climate, and hydrology data are collected and how datasets of other variables are built from primary data. A simple regurgitation of the vast literature about the primary data would not serve the goals of this report. The focus, instead, is on compiling, summarizing, and offering objective assessment of the data and the work that has been done to make it available. The objective of this volume is to be a uniquely useful reference for readers.

Chapter 4 is a reference for weather and climate data. It begins with a description of the methods and equipment that have been used to collect weather data, from the installation of the first weather stations in the basin in the late 1800s, to the emergence of remotely-sensed distributed data. It explains how point data become gridded datasets, how missing data are treated, how large scale data are disaggregated, which datasets have common source data, and how quantitative biases can be introduced. Knowledge about the methods behind, and idiosyncrasies of, the datasets, along with their strengths and weaknesses is presented to help readers determine which data sources are better fits for their applications. The chapter provides a detailed comparison of 11 gridded datasets. It explains things to consider when comparing values and trends from these datasets, and practical and scientific considerations when selecting a gridded dataset.

Chapter 5 is a reference to hydrology data—snowpack, streamflow, soil moisture, evaporation, and evapotranspiration—that are key inputs to streamflow forecasting and system modeling. Snowpack, soil moisture, and evaporation/evapotranspiration data are all gathered using three methods—in situ measurements, modeled estimates, and remote sensing. Chapter 5 provides a comprehensive description of the multiple data sets developed by each method, and an explanation of the advantages and limitations of each. Streamflow, on the other hand, has been measured in essentially the same way across the basin since measurements commenced at the end of the 19th century: stream gages that measure stream stage, which is subsequently translated to flow by a rating curve that is essentially an empirical hydraulic model of the gage site. This chapter explains the uncertainties in the gage record, which arise from measurement error but to a larger degree from errors in the rating curves. Measured streamflows are naturalized or deregulated for use in models. This process introduces more uncertainty, and the sources and implications of this uncertainty are thoroughly described in this chapter. The chapter closes with a summary of challenges and opportunities regarding hydrology data.

Chapter 6 is devoted to describing the evolution, application, and trade-offs of a number of runoff and land surface models that are the foundation of applications at the smallest time scale, streamflow forecasting, to the largest time scale, climate change projections. This chapter is complemented by Chapters 8 and 11, which place hydrology models in the context of forecasting and projection applications, and by Chapters 4 and 5, which describe the provenance and qualities of the data used to force and validate hydrology models. The advantages and disadvantages of the hydrology models are summarized and their usefulness for either forecasting or simulating climate sensitivity or both is assessed. Not surprisingly, the evolution of hydrologic models follows a path of increasing complexity, from empirical conceptual runoff models, to simple water balance models, which led to distributed land surface models and fine-scale physically explicit models and finally to coupled land-atmosphere models. Models of all of these types continue to be applied in the basin, and Chapter 6 describes the models currently in use in the basin and explores emerging models and approaches that could improve forecasting and projection. The chapter closes with an examination of knowledge gaps, challenges and opportunities for improvement.



Chapter 4

Observations—Weather and Climate

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Key points

- Weather and climate data are collected and interpolated for specific reasons, so not all data and datasets are suitable for all uses. Users should be cautious about “off-label” use of climate data and should thoroughly investigate the suitability of data before it is applied outside of its planned uses.
- Users of weather and climate datasets should be aware that the data reflect average or summary conditions over their spatial and temporal resolution and should not expect a gridded product to accurately reflect conditions at any particular point on the landscape at any given point in time. This is particularly true for high-relief landscapes like the Colorado River Basin.
- Most of the existing high-resolution gridded datasets share some base information or use similar processing, or both, so they are not strictly independent.
- There is not now, and likely never will be, perfect weather and climate data. Producers of climate information need to communicate, and users should be cognizant of, the strengths and weaknesses of the data they choose and how climate data choices influence their conclusions.
- In the Colorado River Basin, the highest elevations have the lowest weather station densities and likely the least precise and accurate weather information. This is especially problematic for water resource questions, because such a large fraction of the runoff is generated at high elevations.

4.1 Introduction

Weather and climate are important drivers of many hydrologic processes and thus have a profound influence on water availability in the Colorado River Basin (Nash and Gleick 1991; Christensen et al. 2004; Barnett and Pierce 2009; Rasmussen et al. 2011; Vano, Das, and Lettenmaier 2012). There is increasing awareness of the fact that weather and climate also influence water demand for agricultural (Wisser et al. 2008), municipal (Kenney et al. 2008), and industrial (van Vliet et al. 2016) uses. Accordingly, any assessment of hydrologic variability in the Colorado River Basin must consider the underlying weather and climate variability in spatially and temporally explicit ways, which makes climate data and datasets (gridded interpolations of station observations and potentially other information) particularly critical.

Most climate data were initially collected in the context of weather observation in particular locations and largely for specific reasons, such as assessing irrigation demand, evaluating water supply, or ensuring aviation safety (Tables 4.1 and 4.2). These primarily purpose-driven measurements,

however, are now used in much broader ways. As part of spatially extensive networks, long-term records are used to understand spatio-temporal variability in climate and in the hydrologic processes it influences.

Table 4.1

Planned uses and operating agencies for station networks commonly used in hydrologic research within the Colorado River Basin.

Network/Operating Agency	Planned Uses	Citations and Information
Cooperative Observer Program (COOP)	Routine weather and climate monitoring to track changes, improve forecasts, and assist with public safety	National Oceanic and Atmospheric Administration (NOAA) 2019; National Weather Service (NWS), n.d.; Iowa State University, n.d.
NWS via volunteers		
Automated Surface Observing System/Automated Weather Observing System (ASOS/AWOS)	Aviation, weather monitoring	National Weather Service (NWS), n.d.; Iowa State University, n.d.; National Oceanic and Atmospheric Administration (NOAA), n.d.; Federal Aviation Administration (FAA) 2019; National Oceanic and Atmospheric Administration (NOAA), n.d.; Iowa State University, n.d.
NWS/FAA		
Snow Telemetry Network (SNOTEL)	Monitoring snow for water resources	Schaefer and Paetzold 2001; Natural Resource Conservation Service (NRCS), n.d.
NRCS		
Remote Automated Weather Station Network (RAWS)	Fire weather (primarily)	Zachariassen et al. 2003; Western Regional Climate Center (WRCC), n.d.; National Interagency Fire Center (NIFC), n.d.
USFS, BLM, NPS, BIA, FEMA, FWS, state		
Cooperative Agricultural Weather Network (AgriMET)	Agriculture; ET calculation	Reclamation 2019a
Reclamation		
Colorado Mesonet (CoAgMET)	Agriculture; ET calculation	Colorado State University (CSU) 2019
Colorado Climate Center at CSU		
Soil Climate Analysis Network (SCAN)	Agriculture; ET calculation	Schaefer and Paetzold 2001; Natural Resource Conservation Service (NRCS), n.d.; Iowa State University, n.d.
NRCS		

Network/Operating Agency	Planned Uses	Citations and Information
Community Collaborative Rain, Hail and Snow Network (CoCoRaHS)	Precipitation measurement	Doesken and Reges 2010; Reges et al. 2016; “CoCoRaHS: Community Collaborative Rain, Hail & Snow Network” n.d.
Colorado Climate Center at Colorado State University via volunteers		
US Climate Reference Network (USCRN)	Long-term climate monitoring	NOAA National Centers for Environmental Information n.d.; NOAA National Environmental, Satellite, Data, and Information Service 2007; Diamond et al. 2013
NOAA		

For many purposes, however, weather station data are not sufficient. Individual station records can contain gaps when measurements were not made. Moreover, there is incomplete spatial coverage. To resolve these problems, point weather data have been used to develop gridded data products. In the development of gridded datasets, the landscape is overlain with a grid, and station observations are interpolated or aggregated to estimate a value for each grid cell. This process is carried out at regular time steps (most frequently daily or monthly) for some number of years (e.g., 1950–2010). Because multiple stations—and potentially other types of data—are used in the development of the gridded data, the resulting products are spatially and temporally complete, i.e., there are values for every grid cell and the time series contain no gaps.

Within the Colorado River Basin, weather and climate data are used for a number of purposes. First, weather and climate data are used to calibrate hydrologic and streamflow forecast models used in scientific studies and for water resource management decisions. Once these models have been calibrated, weather and climate data are used as inputs to drive them. Climate data, particularly gridded datasets, have also been used extensively to downscale and bias-correct climate model projections that are then used as inputs to hydrologic models. The output from these future simulations is then used in a variety of ways to assess the reliability of water supplies in the Colorado River Basin under a range of future climate conditions (Vano, Das, and Lettenmaier 2012; Vano and Lettenmaier 2014; Ayers et al. 2016). In addition to their use as model inputs, compiled weather data have been used to analyze climate patterns and trends across the basin (Hidalgo and Dracup 2003; Mo, Schemm, and Yoo 2009; Nowak et al. 2012) and to better understand historical patterns of hydrologic variability (McCabe and Wolock 2007; Woodhouse et al. 2016; McCabe et al. 2017). Climate data have also been used in the analysis and calibration of paleoclimate proxies, primarily tree rings, that then provide long-term histories of streamflow,

temperature, precipitation, and snow in the basin (Meko et al. 2007; Woodhouse and Pederson 2018).

Table 4.2

General information about station networks commonly used in hydrologic research within the Colorado River Basin. Network start year indicates the earliest available data collected, but not all stations in the network have coverage back to the start of the network. The “Available Variables” column describes the most common variables available from the network, although there can be data gaps, and some stations may provide additional variables.

Network	Available Variables	Minimum Temporal Resolution	Network Start Year
Cooperative Observer Program (COOP)	Maximum temperature, minimum temperature, snowfall, precipitation	Daily	1890
Automated Surface Observing System/Automated Weather Observing System (ASOS/AWOS)	Temperature, pressure, wind, dewpoint, precipitation (type, amount, intensity), visibility, ceiling height, other comments	Hourly or sub-hourly; some stations collect 1- and 5-minute observations	ASOS: late 1980s/1990s, AWOS implemented earlier
Snow Telemetry Network (SNOTEL)	Temperature, precipitation, snow water equivalent. Usually also solar radiation, snow depth, wind, humidity; subset of stations: soil moisture and temperature	Sub-daily; some stations are hourly	1979
Remote Automated Weather Station Network (RAWS)	Precipitation, wind, air temperature, humidity, fuel temperature, fuel moisture, solar radiation	10-minute	Late 1970s, early 1980s
Cooperative Agricultural Weather Network (AgriMET)	Temperature, precipitation, humidity, soil temperature and moisture, wind, radiation	Some variables at 15 minutes	Early 1980s
Colorado Mesonet (CoAgMET)	Temperature, humidity, wind, radiation, precipitation, soil temperature	5-minute	Early 1990s
Soil Climate Analysis Network (SCAN)	Soil temperature and moisture, humidity, wind, radiation, precipitation, temperature	Hourly	Early 1990s
Community Collaborative Rain, Hail and Snow Network (CoCoRaHS)	Precipitation, snowfall, hail, and flood reports; some evapotranspiration	Daily	1998
US Climate Reference Network (USCRN)	Temperature, precipitation, wind speed, humidity, radiation, soil temperature and moisture	Hourly	2003

Numerous approaches have been taken to provide these data in ways that meet diverse user needs. Most data products fall into one of four main categories: 1) in situ point data collected at weather stations, 2) statistically interpolated data, 3) physically interpolated data (i.e., reanalyses), and 4) spatially continuous data derived from a remotely sensed product. This chapter focuses on in situ data and statistically interpolated data, as these are the kinds of data that have been used most frequently to understand the hydrology of the basin. However, one product discussed here, the North American Land Data Assimilation Scheme (NLDAS-2) is derived from reanalysis (Xia et al. 2012).

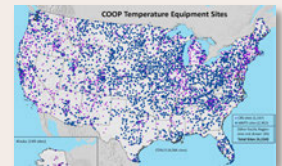
4.2 In situ observations

In situ weather station data are simply records of weather variables (e.g., temperature and precipitation) at specific locations. These stations are the underlying source of all weather and climate information from the late 1800s, when the first weather stations were installed in the Colorado River Basin, until the late 20th century, when remotely sensed climate monitoring from satellites first became widely available (Davis 2007). Although the first weather stations in the basin were put into place in the late 1800s, there were relatively few stations, and their spatial coverage was quite limited (Figure 4.1). As the number of stations has increased over time, their spatial distribution has increased, as has the diversity of environments that they sample in the basin (McAfee et al. 2019). That said, weather station coverage is still more complete in river valleys where towns and cities are located, and few high-quality stations were installed at high elevations prior to the late 1970s or early 1980s (McAfee et al. 2019).

Weather recording technology has also changed over time. Figure 4.2a shows a COOP station in Granger, Utah from around 1930. Temperature is measured inside a Cotton Region Shelter with a liquid thermometer. While [some COOP](#) stations still use these sensors, others use an electronic thermometer referred to as Maximum Minimum Temperature System or MMTS inside a shield composed of white plates. Both can be seen in Figure 4.2b, the COOP station in Logan at Utah State University. Automated Weather Observing System, or ASOS, stations (Figure 4.2c) also use electronic temperature sensors.

Almost all weather stations record daily minimum and maximum temperature and daily precipitation (the total liquid content of all rain, snow, and other precipitation that accumulates in a rain gage). The intended or primary use of the station dictates where it is located, what other variables it measures, and the temporal resolution of those data.

NWS Cooperative Observer Program



Link:

<https://www.weather.gov/coop/>

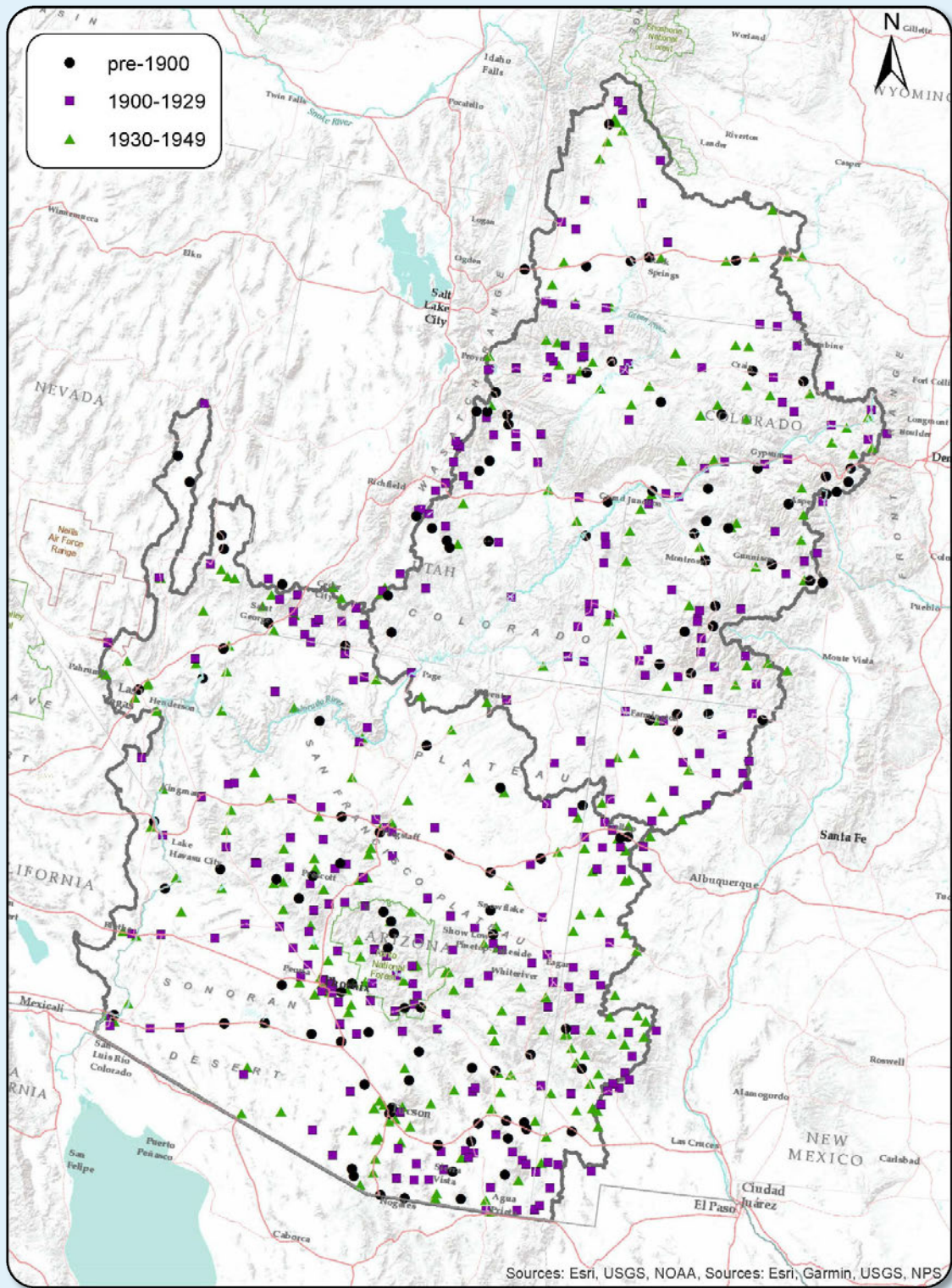


Figure 4.1

Map showing stations from the Global Historical Climatology Network located in or near the Colorado River Basin that have first record dates prior to 1950.

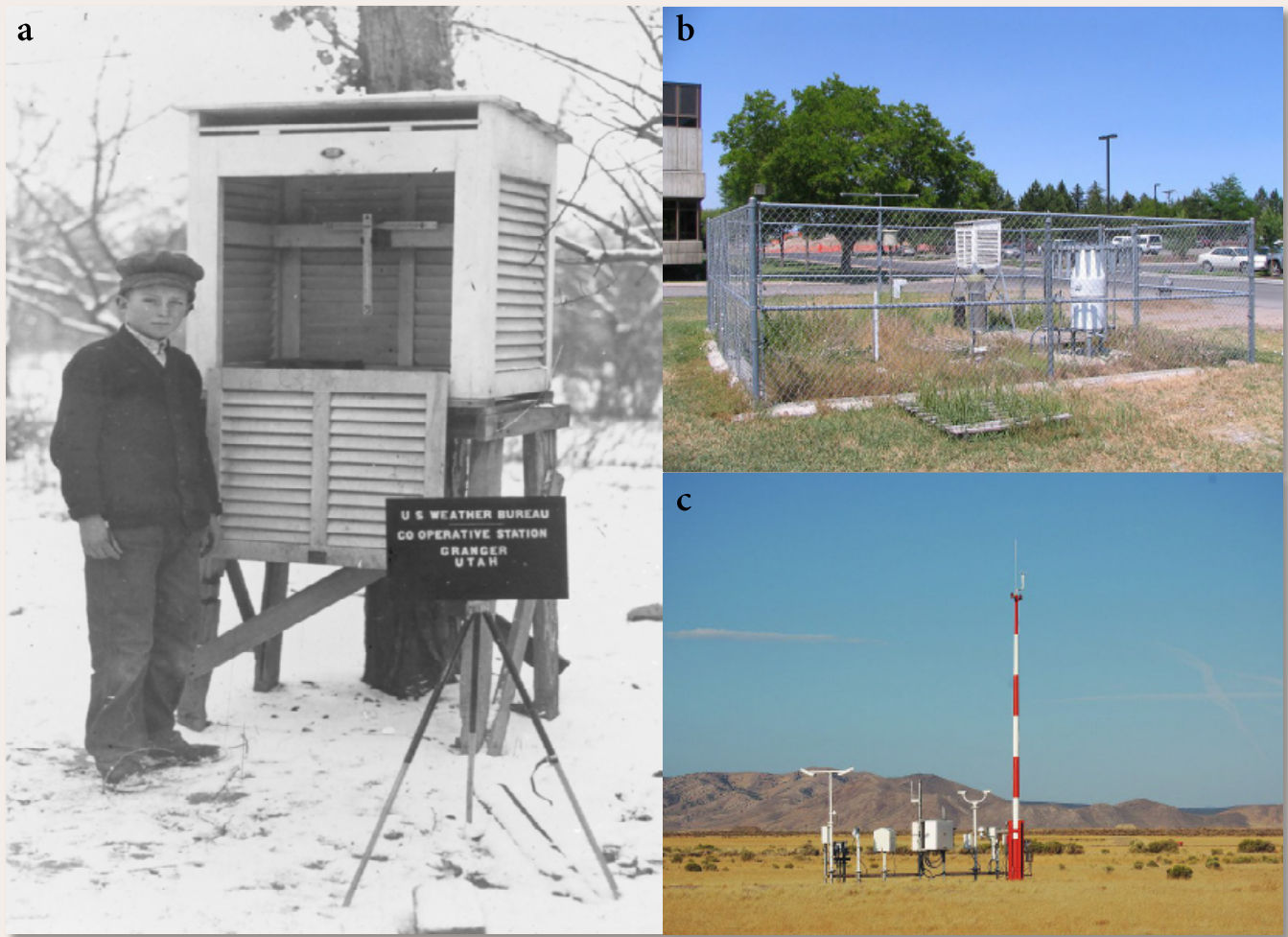


Figure 4.2

Photos of (a) a COOP station in Granger, UT, taken around 1930, (b) the COOP station at Utah State University which measures temperatures using both a Cotton Region Shelter and the Minimum Maximum Temperature System. (c) the ASOS station at Milford, UT. Panel [a](#) is from the NOAA Photo Library. Panels [b](#) and [c](#) are from the Western Regional Climate Center Station Pictures resource.

The need to monitor for specific reasons has led to the development of specific weather station networks—collections of stations using very similar instrumentation designed to measure weather for an explicit purpose. For example, the SNOTEL network was developed primarily to assess water resource availability in the western United States (Schaefer and Paetzold 2001). (It is possible for a station to belong to multiple networks. For example, the weather station at Grand Junction Walker Field is an ASOS station that also belongs to the COOP network.)

Because much of the western U.S. relies on water delivered as winter precipitation and stored in mountain snowpacks (e.g., Christensen et al.

2004), stations in the SNOTEL network are typically located in small valleys in the mountains, where snow collects (Schaefer and Paetzold 2001). Stations are instrumented to provide multiple measurements of the snowpack such as snowfall, snow depth, and snow water equivalent (SWE) that are not routinely measured at other networks. They are also often designed to function in areas with deep snow by, for example, measuring precipitation at heights well above 6 feet, although the World Meteorological Organization notes that most gages are placed about 3 feet above the surface (World Meteorological Organization 2008). Normally, the use of tall rain gages would enhance undercatch, because wind speeds increase with height; however, this may not influence the degree of undercatch at SNOTEL stations because many SNOTEL sites are forested (Serreze et al. 1999). Figure 4.3 shows the Arapaho Ridge SNOTEL station in Colorado. The view of the rain gage relative to the surrounding vegetation suggests that the gage is taller than three feet. The SNOTEL station also includes a snow-depth sensor and a snow pillow, equipment that is relatively standard for SNOTEL stations but not common in other weather station networks.



Figure 4.3

Photo of the Arapaho Ridge SNOTEL site northwest of Longs Peak in Colorado. (Source: Brian Domonkos, Natural Resources Conservation Service)

Tables 4.1 and 4.2 describe the characteristics of seven station networks that are common across the western U.S. and that are frequently used to understand hydrology and consumer demand in the Colorado River Basin. These tables are not comprehensive; there are smaller and more localized networks that may also be used in hydrologic analyses. In some cases, data from smaller networks are provided via similar, more comprehensive

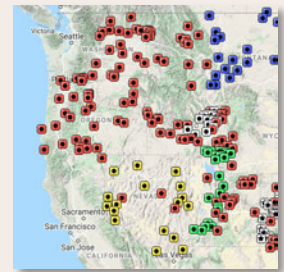
networks. For example, the AgriMet [webpage](#) provides access to data from NICENet, AgWxNet, and some state-run stations that provide similar kinds of measurements (Reclamation 2019a).

Figure 4.4 shows stations in or within 6.2 miles (10 km) of the basin in the Soil Climate Analysis Network (SCAN), and the AgriMET, CoAgMet, SNOTEL, RAWS, and COOP networks. Only stations that reported in the 21st century (i.e., stations that have an end date later than 2000) are shown. RAWS and COOP station locations were identified from the Global Historical Climatology Network (GHCN) database on the basis of their identification codes. The GHCN is an extensive collection of global weather station data that meet minimum criteria for record length and metadata (Menne et al. 2012). Station records included within the GHCN are subjected to automated quality control and assurance checks (Peterson, Vose, et al. 1998; Durre et al. 2010).

Although different station networks were developed for different purposes, all station data are prone to a common set of errors. Missing data is a common problem that occurs at both manual and automated stations because of equipment malfunction and reporting failures. Station records are also prone to inhomogeneities—non-climatic changes in the mean or variance of the data—caused by changes in instrumentation, time of observation, local surroundings, and even observers, as well as by relocation of the entire station (Karl et al. 1986; Karl, Diaz, and Kukla 1988; Quayle et al. 1991; Peterson, Easterling, et al. 1998; Menne and Williams 2009; Menne, Williams, and Vose 2009). Some of these inhomogeneities are correctable, and some are not. One notable recent example of this is the inhomogeneity in minimum temperature at SNOTEL sites caused by a network-wide changeover to new thermometers beginning in the mid-1990s and extending through the early 2000s (Oyler, Dobrowski, et al. 2015).

In Colorado, the change in instrumentation occurred primarily in 2004–2006 (Rangwala et al. 2015). The change in instrumentation led to the appearance of rapidly warming minimum but not maximum temperatures and a correspondingly sharp reduction in the daily temperature range (Rangwala et al. 2015). This particular inhomogeneity appears to be correctable, either through comparison with near-by stations as in Oyler, Dobrowski, et al. (2015), or through corrections developed by the Natural Resources Conservation Service (Ma 2017). In general, there are any number of mechanisms for correcting inhomogeneities (Menne and Williams 2009; Peterson, Easterling, et al. 1998; Hamlet and Lettenmaier 2005), most of which rely on the presence of a nearby station with a homogenous record. Inhomogeneities may be more difficult to correct in areas where, or during times when, there are few weather stations to compare the suspect station against.

USBR Agrimet Network Map



Link:

<https://www.usbr.gov/pn/agrimet/agrimetmap/agrimap.html>

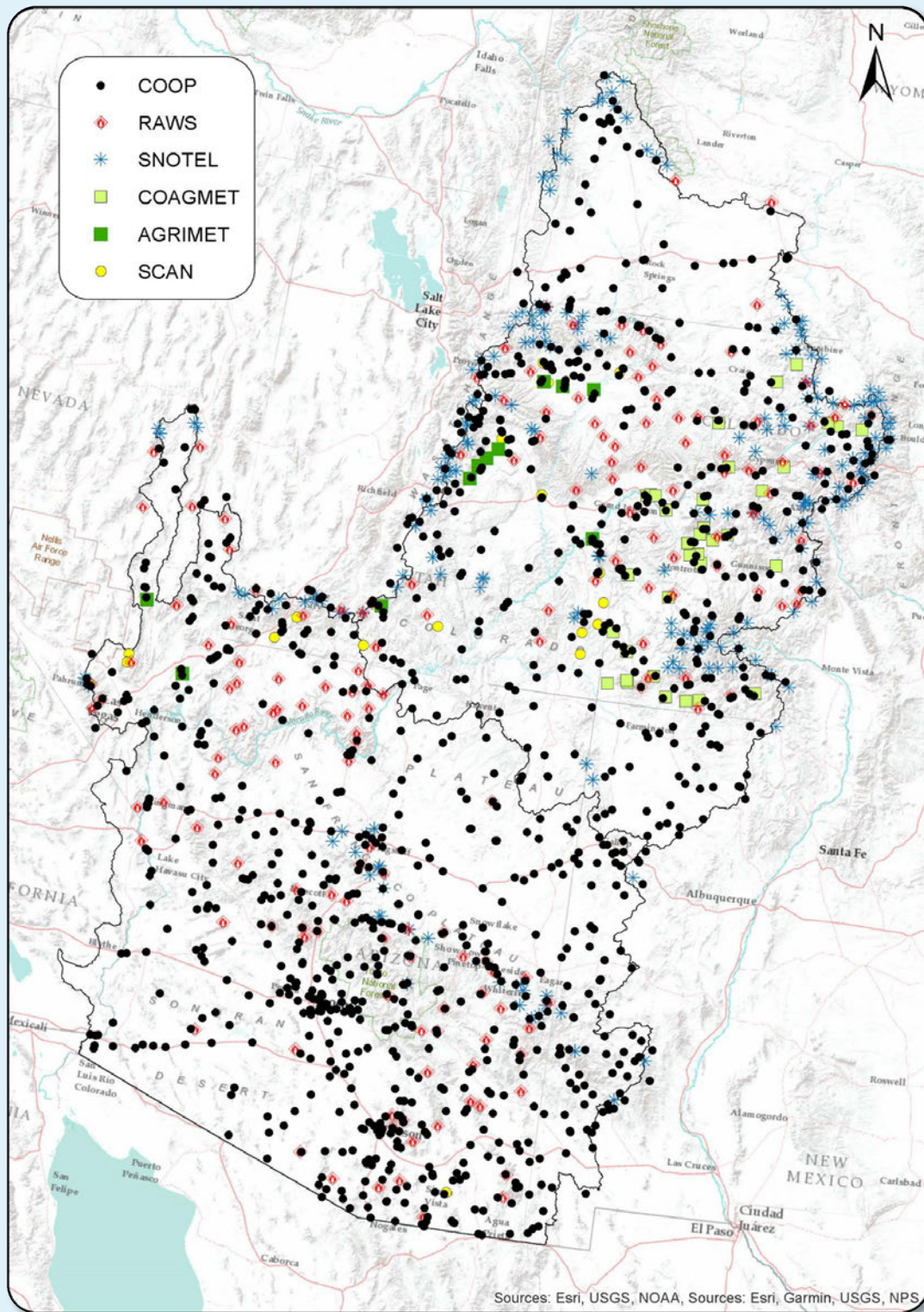


Figure 4.4

Locations of presumably active weather stations in or near the Colorado River Basin. COOP and RAWS locations were derived from the GHCN, so COOP and RAWS stations not included in the GHCN are not shown on the map. Likewise, stations in the COOP network but that are also ASOS or AWOS stations may not be represented on this map depending on their coding in the GHCN.

Inhomogeneities that develop due to gradual changes in the surrounding environment can be more challenging to adjust for (Menne, Williams, and Vose 2009). The presence of multiple kinds of inhomogeneities in a record, for example, at a station that is moved from one location to another while also being impacted by urbanization, may further complicate correcting the record.

Precipitation measurements are also affected by undercatch, where less precipitation is captured by the gage than actually falls. Undercatch occurs because of 1) evaporation from the gage; 2) wetting error (i.e., water that adheres to the sides of the gage and may not be fully measured); 3) turbulence, wherein turbulent air flow over the mouth of the gage pushes rain drops and snowflakes away from the gage opening; and 4) for snow, bridging across the top of the gage, which makes it more likely that precipitation will be lost before measurement. The last can also shift the apparent timing and intensity of precipitation if snow accumulates over the mouth of the gage only to fall in, all at once, at a later time. The degree of undercatch varies with the type of gage used, the use and kind of shielding, wind speed, precipitation phase, and precipitation intensity (Adam and Lettenmaier 2003; Goodison, Louie, and Yang 1998). Numerous studies have evaluated catch efficiency for a range of gage and shield combinations. A clear finding is that unshielded gages measure less rain and snow than shielded gages (Hanson, Johnson, and Rango 1999; Rasmussen et al. 2012). This may be of concern because some networks, like CoCoRaHS (Reges et al. 2016) and RAWS (National Wildfire Coordinating Group 2014) use unshielded gages. Owing to the high variability in undercatch due to equipment combined with environmental conditions, making accurate correction is difficult, although some attempts have been made (e.g., Yang et al. 1998).

Although rain and snow are particularly difficult to quantify, any meteorological measurement can contain error. Stations that are not regularly maintained and calibrated can collect inaccurate or imprecise data, even in the absence of damage (Leeper, Rennie, and Palecki 2015). As with precipitation, different models of temperature sensors and logging equipment may measure slightly different values (Lin and Hubbard 2004), and different types of shielding on temperature sensors can also modify the temperature observed because they differ in the degree of shading and airflow past the temperature sensor they provide (Hubbard, Lin, and Walter-Shea 2001). Liquid thermometers can also be subject to parallax error (Linacre 1992), for example, when a thermometer at a fixed height is read by observers of different heights. Measurement error associated with other variables is also expected (Linacre 1992). Recording errors of all kinds can also be a problem, particularly for manual stations (Leeper, Rennie, and Palecki 2015; Menne et al. 2012; Linacre 1992).

Consequently, another consideration in the use of station data is whether and in what way the data have been quality controlled (QC) prior to release. Not all networks conduct extensive QC, those that do may use different procedures, and QC protocols may evolve over time. The AgriMet network regularly maintains and calibrates equipment, applies automated checks to sub-daily data collected at its stations, flags potentially erroneous values in near real-time and then uses manual checks daily (Hamel, n.d.). The SNOTEL network also relies on a combination of equipment maintenance, flagging, and eyes-on evaluations of data (Kuiper et al. 2014). Other networks, such as RAWS, may have less standardized quality control (Zachariassen et al. 2003; Brown et al. 2011). Integrative networks typically apply their own checks. The Global Historical Climatology Networks investigate data records independently and in relationship to nearby stations, typically flagging suspect data (e.g., Global Historical Climatology Network; Durre et al. 2010; Menne et al. 2012).

In general, in situ weather station data are most appropriate for characterizing the climate variables they were designed to measure in their immediate surroundings, assuming that they are routinely and appropriately maintained. However, many stations have proven to be useful outside of their intended purpose, especially when analyzed in innovative ways. For example, SNOTEL stations are designed primarily to describe the depth and water content of the snowpack, understand how it developed over the course of the season, and track year-to-year variability in the snowpack at that location. Although SNOTEL stations were not necessarily designed for long-term climate monitoring, they are generally well maintained stations that, barring the instrumentation-related inhomogeneity, would be effective in tracking temperature trends in higher elevations. RAWS stations have been used for a much larger array of applications than originally intended (Brown et al. 2011). [AgriMet stations](#) are not designed to track snowpack, most notably because they are not usually instrumented with a snow pillow and snow-depth sensor. They are, however, equipped with both tipping bucket and weighing precipitation gages. When both types of precipitation measurements are available, they can be leveraged to effectively distinguish rain and snow (Strachan 2016). In other cases, beneficial uses have been identified for what would otherwise be errors or weaknesses. For example, the placement of COOP stations in populated areas has diminished their ability to track regional climate variability (without correction), but it has allowed the detection and quantification of urban heat islands.

AgriMet Weather Station Equipment and Sensors



Link:

<https://www.usbr.gov/pn/agrimet/aginfo/sensors.html>

4.3 Statistically interpolated gridded data

Statistically interpolated data fill spatial gaps between existing point measurements using a variety of techniques. Most statistically interpolated data are aggregated to represent grids or rasters of varying spatial resolution; however, there are some climate data provided not for regular grids, but for irregular areas like climate divisions, counties, or basins. Some of these irregular area products are themselves developed from gridded products. For example, the latest (2019) version of the climate division data are derived from a roughly 3.1-mi (5-km) resolution gridded product called nClimGrid (Vose et al. 2014).

The interpolation used to make gridded data may be based solely on observations, with the value at a given point based on some, usually distance weighted, function of values at nearby stations. This is more common for coarser resolution ($> 0.5^\circ$) products. Most higher-resolution (< 10 -mile) products, however, also incorporate some physiographic information to more accurately reflect the strong influence of terrain on spatial variability in climate. For example, all of the products described in this chapter incorporate an adjustment for the lapse rate or expected decrease in temperature with elevation. Different statistical methods for interpolation are used in different products. Although they are not discussed here, Daly (2006) provides an overview of commonly used interpolation methods.

Gridded data products

For most hydrologic modeling applications, relatively high-resolution gridded data are preferable, so the focus here is on selected, commonly used products listed in Table 4.3 and described in Table 4.4.

Table 4.3

General information about gridded data products commonly used in hydrologic research within the Colorado River Basin. Definitions are provided in the glossary.

Product Name	Variables	Spatial Resolution	Spatial Coverage	Temporal Resolution	Temporal Coverage
PRISM AN81d	Tmax, Tmin, Tmean, Tdew, VPDmax, VPDmin, Prcp	30 sec (~0.5 mi) & 2.5 min (~2.5 mi)	CONUS	Daily	1981–near present
PRISM AN81m	Tmax, Tmin, Tmean, Tdew, VPDmax, VPDmin, Prcp	30 sec (~0.5 mi) & 2.5 min (~2.5 mi)	CONUS	Monthly	1895–near present
PRISM LT81m	Tmax, Tmin, Tmean, Tdew, VPDmax, VPDmin, Prcp, VPR	30 sec (~0.5 mi)	CONUS	Monthly	1895–near present
TopoWx	Tmax, Tmin	30 sec (~0.5 mi)	CONUS	Daily, monthly	1948–2016

Product Name	Variables	Spatial Resolution	Spatial Coverage	Temporal Resolution	Temporal Coverage
Livneh 2013/ Maurer 2002	Tmax, Tmin, Prcp, Wind, SolRad & VIC-simulated baseflow, canopy water, ground heat flux, sensible heat flux, latent heat flux, net radiation, SWE, soil moisture, surface runoff, total ET	L: 1/16° (~3.8 mi) M: 1/8° (~7.5 mi)	CONUS & Columbia River Basin	Sub-daily, Daily, monthly	L: 1915–2011 M: 1950–2000
Livneh 2015	Tmax, Tmin, Prcp, Wind, SolRad & VIC-simulated baseflow, canopy water, ground heat flux, sensible heat flux, latent heat flux, net radiation, SWE, soil moisture, surface runoff, total ET	1/16° (~3.8 mi)	N. America south of 53°N through Mexico	Daily, monthly	1950–2013
gridMET	Tmax, Tmin, Prcp, RHmin, RHmax, SpecHum, Wind, SolRad & derived burning index, fuel moisture, ERC, PDSI, rET-alfalfa, rET-grass, VPD	2.5 min (~2.5 mi)	CONUS	Daily	1979–very near present
Hamlet 2005	Tmax, Tmin, Prcp, Wind	1/8° (~7.5 mi)	CONUS plus Columbia River Basin	Daily	1915–2003
Hamlet 2010	Tmax, Tmin, Prcp, Wind	1/16° (~3.8 mi)	CONUS plus Columbia River Basin	Daily	1915–2006
Daymet v. 3	Tmax, Tmin, Prcp, SolRad, DayLength, VPR, SWE	1 km (~0.6 mi)	N. America, north of 14°N	Daily	1980–end of last full year
Newman gridded ensembles	Prcp, Tave, DTR	1/8° (~7.5 mi)	CONUS & portions of Mexico and Canada	Daily	1980–2016
nClimGrid	Tmax, Tmin, Prcp	5 km (~3.1 mi)	CONUS	Monthly	1895–present
NLDAS-2	Tave, SpecHum, Prcp, Wind, Pres, SolRad, DLWR, & numerous land-surface model outputs derived from the forcing variables	1/8° (~7.5 mi)	CONUS, parts of Canada and Mexico, (125° to 67°W, 25° to 53°N)	Hourly	1979–near present

[PRISM](#) (Parameter-elevation Relationships on Independent Slopes Model) was one of the first higher-resolution (< 10-mile) gridded climate products (Daly et al. 1994, 1997, 2002, 2008), and it is one of the few to extend back to the late 19th century. Because of its long history and good temporal coverage, PRISM has long been considered a solid climate data choice. It also incorporates one of the most diverse networks of stations (Table 4.4), particularly for precipitation. Many new, higher-resolution gridded products have been developed over the last 10–20 years. Development decisions regarding the spatial and temporal (daily versus monthly) resolution, the time span of the product, and which variables to supply—although most supply only temperature or precipitation, or both—are made to match the product to its intended use and the developers’ assessment of what the underlying data can reasonably support.



Table 4.4

Input data and development methodologies used in the production of commonly used gridded climate datasets.

Product Name Documentation	Input Data	Key methodologies	Notes & Access
PRISM AN81d / PRISM AN81m Daly, Neilson, and Phillips (1994); Daly, Taylor, and Gibson (1997); Daly et al. (2002; 2008); Daly, Smith, and Olson (2015; PRISM 2016)	All networks listed in Table 4.2, plus Canadian and Mexican federal networks, numerous smaller networks, RADAR data, and information from the NCEP/NCAR Reanalysis	Normals are developed using the PRISM methodology, wherein the regression accounts for distance to the coast, elevation, cold-air pooling, and boundary layer thickness. Climatologically aided interpretation is then used to develop the temporally varying datasets. Some radar data also used to inform precipitation.	PRISM aims to make a "best estimate" given available information. Additional details about adjustments between daily and monthly data for different versions of each are provided in PRISM (2016) Table 5. Access: http://www.prism.oregonstate.edu/ (2.5 min, free) prism_orders@nacse.org (30 sec, \$)
PRISM LT81m Daly, Neilson, and Phillips (1994); Daly, Taylor, and Gibson (1997); Daly et al. (2002; 2008); PRISM (2016); Daly, Smith, and Olson (2015)	AGRIMET, ASOS, AWOS & WBAN, COOP, RAWs, SNOTEL, Canadian and Mexican federal networks, and stations run by the H.J. Andrews Experimental Forest, the Western Regional Climate Center, the Minnesota Climatology Working Group, and the North Dakota State Water Commission	Normals are developed using the PRISM methodology, wherein the regression accounts for distance to the coast, elevation, cold-air pooling, and boundary layer thickness. Climatologically aided interpretation is then used to develop the temporally varying datasets. Some information from RADAR is also used to inform precipitation.	The LT81m version aims for "temporal consistency" and so uses only networks with 20+ year records. Access: prism_orders@nacse.org (\$)

Product Name Documentation	Input Data	Key methodologies	Notes & Access
TopoWx Oyler, Dobrowski, et al. (2015); Oyler, Ballantyne, et al. (2015); Oyler et al. (2016); Oyler, n.d.	GHCN-D (incl. COOP, ASOS, WBAN, RAWS, SNOTEL), SNOTEL, RAWS that might not be in GHCN-D. Requires 5+ years data, MODIS LST (MYD11A2)	Station records are homogenized and gap-filled prior to interpolation. A terrain index based on the PRISM DEM is used to predict cold-air pooling. Grids of monthly averages are derived using kriging; geographically weighted regression is used to interpolate daily anomalies, which are added to the monthly averages to get daily values.	Annual updates will incorporate both new observations and model enhancements, resulting in improved datasets, but versions will be incompatible. Access: http://www.scrimhub.org/resources/topowx/ (free)
Livneh 2013/ Maurer 2002 Maurer et al. (2002); Livneh et al. (2013); NOAA ESRL, n.d.; Livneh, n.d.	COOP temperature and precipitation from stations with 20+ years of data. Environment Canada stations in Canada and Mexican Meteorological Service Stations in Mexico, with gap-filling as needed from NCEP/NCAR Reanalysis and GPCP precipitation. Wind from NCEP/NCAR R1. Wind values before 1948 are the average of available years.	Temperatures were adjusted to the elevation of the grid cell before interpolation assuming a constant lapse rate of -6.5°C/km (-3.6°F/1000 ft). Precipitation amounts were adjusted to be consistent with patterns in the 1961-90 PRISM climatology. VIC uses MTCLIM to estimate humidity and radiation variables from temperature and precipitation.	Access: https://www.esrl.noaa.gov/psd/data/gridded/data.livneh.html (free) or http://ciresgroups.colorado.edu/livneh/data/daily-observational-hydrometeorology-data-set-conus-extent-canadian-extent-columbia-river-basin (Livneh, free) http://www.engr.scu.edu/~emaurer/gridded_obs/index_gridded_obs.html (Maurer updated, free)
Livneh 2015 Maurer et al. (2002); Livneh et al. (2013, 2015); Livneh, n.d.	As in Livneh et al. (2013): COOP stations in the U.S. with 20+ years of data, Environment Canada (EC) stations in Canada, Mexican Meteorological Service stations in Mexico	Methods are similar to L13/M02. Precipitation was adjusted to the 1981-2020 PRISM climatology in CONUS and the Vose et al. (2014) climatology in Mexico and Canada.	One of the goals was to reduce spatial inhomogeneities associated with differing national precipitation measurement standards for better hydrologic simulation in transboundary basins. Access: https://data.nodc.noaa.gov/cgi-bin/iso?id=gov.noaa.nodc:0129374;view=html (free) or ftp://192.12.137.7/pub/dcp/archive/OBS/livneh2014.1_16deg/ (free)

Product Name Documentation	Input Data	Key methodologies	Notes & Access
gridMET Abatzoglou (2013; 2019)	NLDAS-2, PRISM, Climate Forecast System Reanalysis for the previous few days to week	Daily NLDAS-2 output is interpolated to the PRISM grid and then temperature, precipitation, and humidity are adjusted to display spatial variability as in PRISM. No higher resolution information is incorporated for any other variable.	Access: http://www.climatologylab.org/gridmet.html (free)
Hamlet 2005 Maurer et al. (2002); Hamlet and Lettenmaier (2005)	Stations with at least one complete year (365 consecutive days) and at least five total years of data from COOP, EC, monthly U.S. Historical Climatology Network (USHCN), Historical Canadian Climate Data (HCCD); Wind from Maurer et al. (2002) where wind values before 1949 are the average of available years.	Smoothed COOP and EC data are adjusted against smoothed homogenized data (USHCN and HCCD) at monthly time scales to account for major inhomogeneities. Elevation adjustment and interpolation as per Maurer et al. (2002) except that the lapse rate was $-6.1^{\circ}\text{C}/\text{km}$ ($-3.3^{\circ}\text{F}/1000$ ft). Precipitation is adjusted to the PRISM climatology.	The goal in Hamlet and Lettenmaier (2005) was to develop a more temporally homogenous dataset otherwise similar to Maurer et al. (2002).
Hamlet 2010 Maurer et al. (2002); Hamlet and Lettenmaier (2005); Deems and Hamlet (2010)	COOP, EC, monthly USHCN, HCCD; Wind from Maurer et al. (2002)	Hamlet 2010 is constructed similarly to Hamlet 2005, but temperature is also adjusted to match the PRISM climatology.	Additional details about the Hamlet 2010 data product were found in Henn et al. 2018 and Lundquist et al. 2015
Daymet v.3 Thornton, Running, and White (1997); Thornton and Running (1999); Thornton, Hasenauer, and White (2000); Thornton et al. (2016)	GHCN	Locally derived elevation relationships and distance weighted regressions are used to estimate Tmax, Tmin, and precipitation. All other variables are estimated as a function of one or more of Tmax, Tmin, and precipitation using MTCLIM algorithms.	Access: https://daymet.ornl.gov/ (free)

Product Name Documentation	Input Data	Key methodologies	Notes & Access
Newman gridded ensembles Clark and Slater (2006); Newman et al. (2015; 2019)	GHCN and SNOTEL stations not included in GCHN	This is developed using the probabilistic interpolation method of Clark and Slater (2006). For each grid point, T, DTR, and P are calculated as a function of distance-weighted station values, latitude, longitude, slope, aspect, and elevation. Uncertainty is gaged from the regression residuals, and then ensemble members are developed by combining the outcome of the regression with a random value generated from the uncertainty and a field of spatially and temporally correlated random numbers.	The goal was to estimate potential uncertainty associated with preparing gridded climate data. Access: https://www.earthsystemgrid.org/dataset/gridded_precip_and_temp.html or https://doi.org/10.5065/D6TH8JR2 (free)
nClimGrid Vose et al. (2014); NOAA, n.d.	GHCN stations in the COOP, ASOS, RAWS, SNOTEL, EC, and Mexican Meteorological Service networks, but only temperature is used from RAWS. Only stations with 10+ years of data since 1950 are included.	Station values are adjusted for known biases, homogenized, and then interpolated in a way that accounts for latitude, longitude, elevation, distance to coast, cold-air pooling, slope, and aspect effects.	This is the gridded data underlying the climate division data nClimDiv. Access: https://data.nodc.noaa.gov/cgi-bin/iso?id=gov.noaa.ncdc:C00332 (free)
NLDAS-2 Cosgrove 2003; Mitchell 2004; Xia et al. 2012	NARR for most variables, CPC and radar for precipitation over U.S. (NARR over Canada and Mexico), satellite data for shortwave radiation augments NARR	Coarse output is interpolated from ~20 mi to ~7.5 mi resolution and temporally interpolated to hours. Temperatures are adjusted assuming a static -6.5°C/km (-3.6°F/1000 ft) lapse rate. Spatial patterns in precipitation are matched to those in PRISM.	Access: https://ldas.gsfc.nasa.gov/nlds/nlds-2-forcing-data and https://disc.gsfc.nasa.gov/datasets?keywords=NLDAS (free)

All of the higher resolution products explicitly account for changes in temperature with elevation, although they do so in different ways (Table 4.4, Figure 4.5). Most products include a mechanism to adjust for changes in precipitation with elevation, as well. Interestingly, many use the elevational change in precipitation estimated by PRISM (Figure 4.6). Other decisions made in the construction of a dataset are typically made to avoid specific problems that arise from changes in the number, type, and location of stations and the common measurement errors described above.

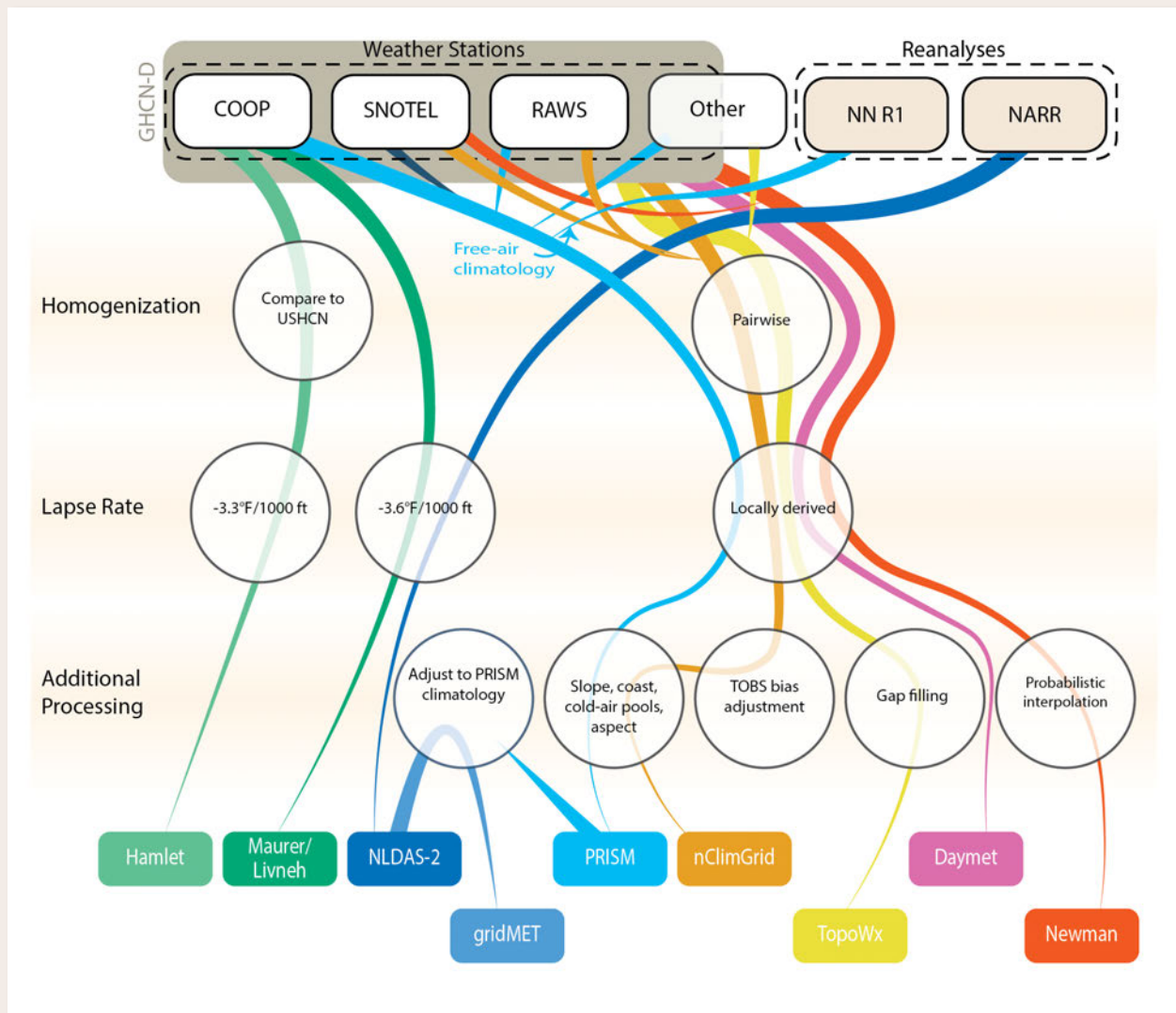


Figure 4.5

Flow diagram of the data sources and processes used to produce the high-resolution gridded temperature products featured in this chapter. Note that the diagram does not accurately indicate the order of processing. For example, gap-filling in TopoWx occurs prior to adjustment for cold-air pooling. In addition to differences in choice of network, products may select different stations from the same network.

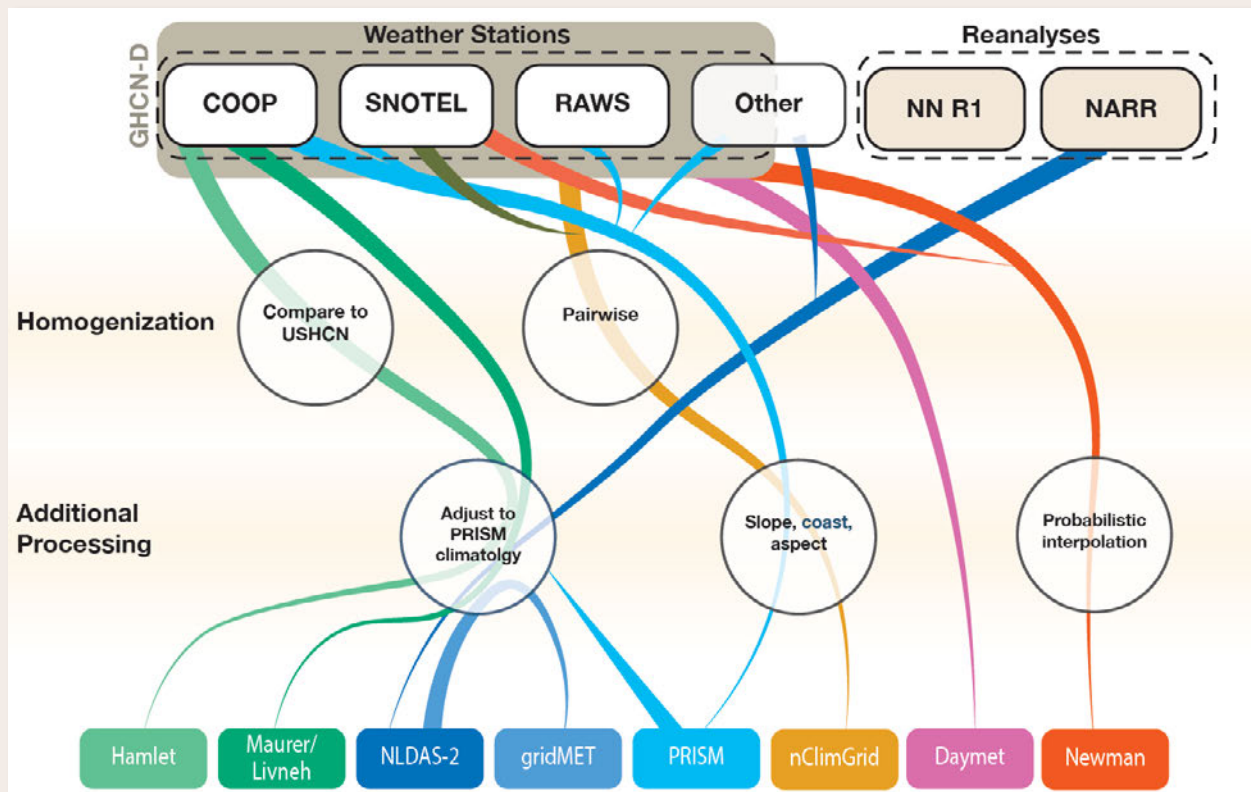


Figure 4.6

Flow diagram of the data sources and processes used to produce the high-resolution gridded precipitation products featured in this chapter. In addition to differences in choice of network, products may select different stations from the same network.

Common choices that must be made in developing a gridded data product include 1) which station network or networks to use, 2) which stations to use from those networks, 3) whether additional data from satellites, radar, or reanalysis is included, 4) what statistical method to use for interpolation, 5) how to account for changes in temperature and precipitation related to elevation, aspect, slope, or other aspects of the terrain, and 6) whether to apply any additional corrections, such as filling gaps in the data, accounting for undercatch, or homogenizing—correcting shifts in the measured climate that are due to changes in the station or the area around the station rather than to actual changes in regional climate.

These choices introduce some disagreement between different products, although there are clear similarities, as well. Figure 4.7 shows time series of average water year minimum and maximum temperature and total water-year precipitation averaged over the Upper Colorado Basin for several of the products listed in Tables 4.3 and 4.4.

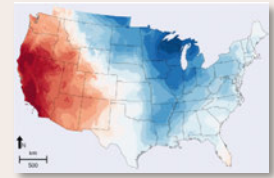
There are clearly strong correlations between the products. All of the datasets that provide precipitation data estimate that basin-wide average water-year precipitation is between 15.5” and 16” (1981–2010 average). They all show that water year 1997 was quite wet—estimates range between 21.0” and 22.1”—and that 2002 was dry—between 9.7” and 10.2”. Earlier in the record, however, there are much larger differences between precipitation estimates. For example, in 1927, the Livneh et al. (2013) data estimate 3.2” more precipitation over the Upper Colorado Basin than PRISM does. Likewise, all of the datasets indicate increasing temperatures since the 1970s. All indicate that 1934 and 2000 were particularly warm years and that the mid-1970s had relatively low minimum temperatures.

These plots also clearly demonstrate that both Livneh datasets estimate substantially cooler minimum temperatures than the other datasets, even though their estimates for maximum temperature are similar to the other data products. Early in the 20th century, the PRISM and nClimGrid data sets provide similar estimates of minimum temperature, but nClimGrid estimates cooler maximum temperatures.

Newman et al. (2019) outline a few common sources of differences between gridded datasets. Numerous other dataset comparison papers such as Behnke et al. (2016), Henn et al. (2018) Lundquist et al. (2015), and Walton and Hall (2018) also discuss the source of discrepancies between data products. One of these is the choice of which weather stations to use. Products that use more weather stations or a more spatially diverse set of weather stations are more likely to capture detailed spatial patterns in temperature and precipitation. Almost all of the products rely directly or indirectly on data from the COOP network, although they may not sample the same stations owing to differences in selection criteria. Exactly which stations are chosen in any area by any product may not be clear without in-depth inspection of the documentation or correspondence with the data developers. For more discussion on this, see Guentchev, Barsugli, and Eischeid (2010) and Newman et al. (2019).

Other choices made in developing gridded datasets also clearly influence the outcome. Gridded datasets, like the Livneh data, that use a fixed lapse rate of $-3.6^{\circ}\text{F}/1000$ feet ($-6.5^{\circ}\text{C}/\text{km}$) tend to estimate colder temperatures, especially colder minimum temperatures and particularly during the winter when cold air pooling is common, than other products (Newman et al. 2015), as can be seen in Figure 4.7. Other choices probably also cause differences between different datasets, but it is not always possible to draw clear lines between those choices (e.g., statistical interpolation method) and the results (Newman et al. 2019). Products like that described in Newman et al. (2015) use “probabilistic interpolation” to account for uncertainty by producing multiple reasonable spatial patterns of temperature and precipitation for each time step.

TopoWx



Link:

<http://www.scrimhub.org/resources/topowx/>

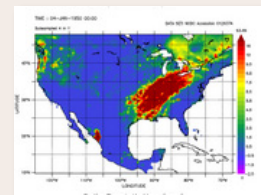
Livneh 2013/Maurer 2002



Link:

<https://www.esrl.noaa.gov/psd/data/gridded/data.livneh.html>

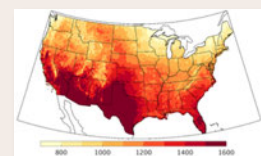
Livneh 2015



Link:

<https://data.nodc.noaa.gov/cgi-bin/iso?id=gov.noaa.nodc:0129374;view=html>

gridMET



Link:

<http://www.climatologylab.org/gridmet.html>

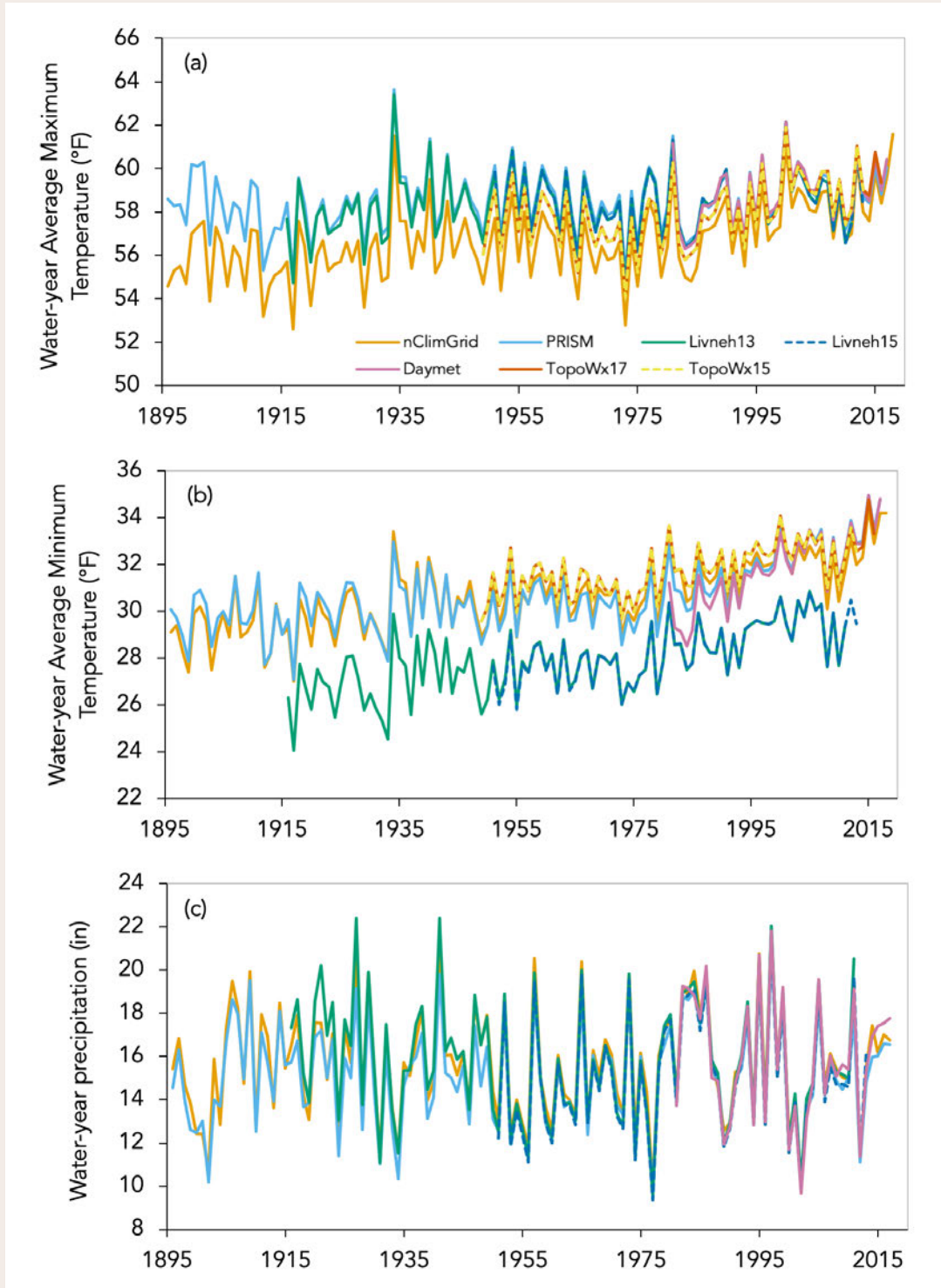


Figure 4.7

Time series of average water-year maximum (a) and minimum (b) temperature and water-year total precipitation (c) averaged over the Upper Colorado Basin. Note that Livneh15 provides monthly precipitation data as the average of the daily precipitation rate. Monthly totals were calculated by multiplying the daily rate by the number of the days in each month, ignoring February 29 in leap years.

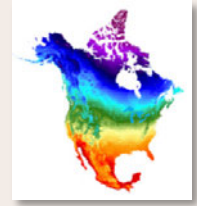
Tables 4.3 and 4.4 describe the characteristics of 11 statistically interpolated gridded products that are commonly used for hydrologic applications in the western U.S. Despite disagreeing in some ways, these gridded products are also not entirely independent. Because the number of weather stations is limited, particularly at higher elevations, most products share at least some base information. There can also be closer interrelationships between products. For example, the Livneh et al. (2013) product uses the Maurer et al. (2002) methodology and is, in fact, billed as an “update and extension” of the earlier effort.

Livneh et al. (2015) uses those same methods for temperature, with additional data from Mexico and southern Canada to produce a gridded product with coverage for all of North America south of 53°N. As a result, their estimates of water-year average temperature over the Upper Basin are nearly identical—the largest difference between the two is 0.24°F in minimum temperature, while differences in maximum temperature are even smaller. GridMET is made by taking the 1/8° (7.5-mi, 12-km) resolution North American Land Data Assimilation System (NLDAS-2) reanalysis and downscaling it to 2.5mi (4 km), using PRISM to guide the interpolation (Abatzoglou 2013). Thus, temporal variability in gridMET will track that in NLDAS-2, while its spatial patterns should be very similar, if not identical, to those in PRISM.

As noted above and shown in Figure 4.6, many products account for fine-scale spatial patterns in precipitation by adjusting their precipitation patterns to match those in PRISM. Among the eight products mapped in Figure 4.6, only Daymet and Newman do not use PRISM to adjust precipitation for elevation (TopoWx does not produce precipitation estimates). Henn et al. (2018) note that PRISM is used to adjust the spatial variability of precipitation in data produced by Livneh et al. (2013, 2015), Maurer et al. (2002), Hamlet and Lettenmaier (2005), Deems and Hamlet (2010), NLDAS-2 (Cosgrove 2003; Mitchell 2004; Xia et al. 2012), and the Climate Prediction Center (CPC) unified gage-based analysis of daily precipitation (Higgins et al. 2000). Interestingly, NLDAS-2 incorporates CPC precipitation early in product development (Cosgrove 2003; Mitchell 2004; Xia et al. 2012), so NLDAS-2 uses PRISM precipitation once indirectly and once directly. GridMET, which further downscales NLDAS-2 to PRISM, essentially uses PRISM to adjust precipitation three times (Abatzoglou 2013).

Fewer gridded products provide information on climate variables such as wind, humidity, and radiation. Wind is an essential variable in hydrology. It is critical for assessing snow redistribution (Liston and Elder 2006). It is also required to accurately estimate evapotranspiration. Hobbins et al. (2012) noted that winds are particularly important in driving evapotranspiration over parts of the Colorado River Basin during the spring

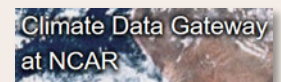
Daymet



Link:

<https://daymet.ornl.gov>

Newman



Link:

https://www.earthsystemgrid.org/dataset/gridded_precip_and_temp.html

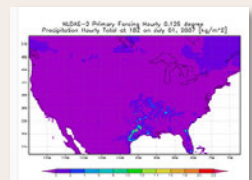
NClimGrid



Link:

<https://data.nodc.noaa.gov/cgi-bin/iso?id=gov.noaa.ncdc:C00332>

NLDAS-2



Link:

<https://data.nodc.noaa.gov/cgi-bin/iso?id=gov.noaa.ncdc:0129374;view=html>

and summer. Yet gridded wind variables are among the least certain and robust of all climate variables. Figure 4.8 shows the development pathways for wind in the datasets evaluated here. Essentially all wind variables in high-resolution data products are derived from the NCEP/NCAR Reanalysis (Kalnay et al. 1996; Maurer et al. 2002; Hamlet and Lettenmaier 2005; Deems and Hamlet 2010; Livneh et al. 2013; 2015) or from the North American Regional Reanalysis (Mesinger et al. 2006; Cosgrove 2003; Mitchell 2004; Xia et al. 2012; Abatzoglou 2013). Because there are few, if any, higher resolution wind products to correct against, most high-resolution wind estimates do not actually contain any high-resolution patterns in wind. They simply reproduce the coarse winds in smaller grid boxes.

Dataset developers encounter similar problems in constructing high-resolution fields of radiation and humidity (Figure 4.9). The gridMET dataset interpolates NLDAS-2 humidity and radiation outputs without any additional adjustment (Abatzoglou 2013). The Daymet, Maurer, and Livneh datasets all use some formulation of the MTCLIM algorithm (Thornton, Running, and White 1997; Thornton and Running 1999; Thornton, Hasenauer, and White 2000) to estimate humidity and radiation from temperature. PRISM provides humidity estimates (dewpoint temperature and vapor pressure deficit), but not radiation, calculated from station-measured relative humidity and air temperature (Daly, Smith, and Olson 2015).

CBRFC use of weather observations and gridded data

As described in Chapters 5, 6 and 8, the Colorado Basin River Forecast Center (CBRFC) forecast model system requires values for temperature and precipitation that are area-averaged for each forecast zone (an elevation band within a catchment) represented in the model. The CBRFC generates these mean areal temperature (MAT) and precipitation (MAP) values for each forecast zone in real-time to drive the daily production of seasonal water supply forecasts and the daily (sometimes sub-daily) production of short-range (1-10 days) streamflow forecasts. The CBRFC has also generated them retrospectively, to create a historical dataset (1981-2015) that is used for forecast model calibration and verification. In both cases, the precipitation values are much more important to the forecast outcomes than the temperature values, and thus greater attention is given to the precipitation input data. The approach used to generate the MAT and MAP values has some commonalities with the gridded products described above, although the final real-time inputs (meteorological forcings) used to drive the CBRFC forecast models are spatially “lumped” and not on a uniform grid like the gridded products described above. The CBRFC endeavors to make the real-time data and the historical calibration data as similar as possible, so that the forecast model is trained on data that is comparable to, if not identical to, what it sees in real-time.

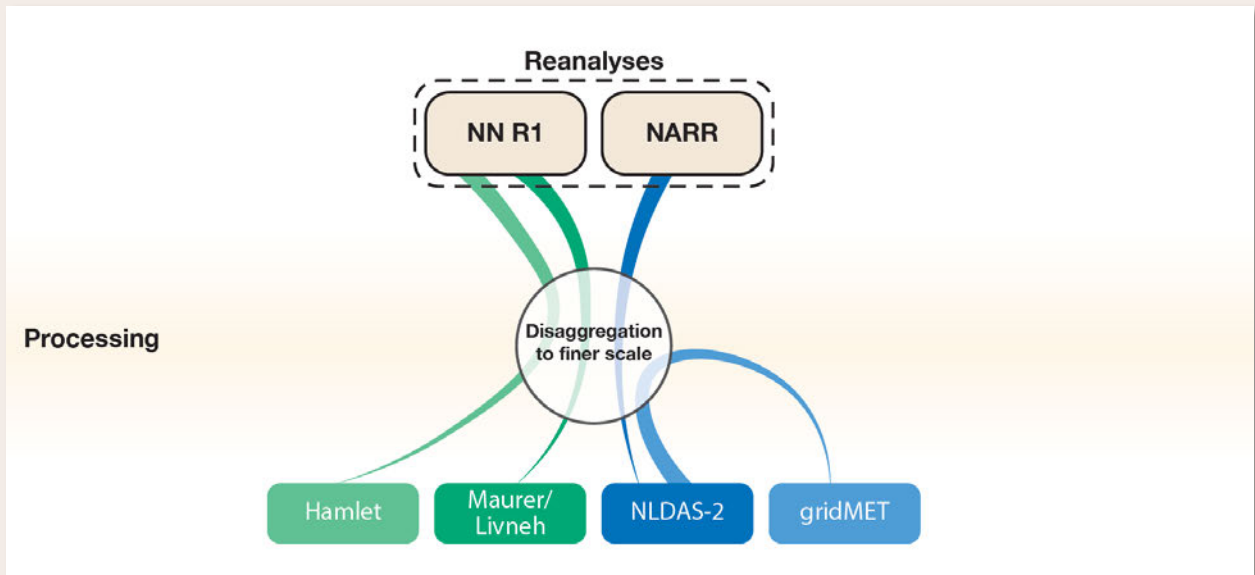


Figure 4.8

Flow diagram of the data sources and processes used to produce the high-resolution gridded wind products featured here.

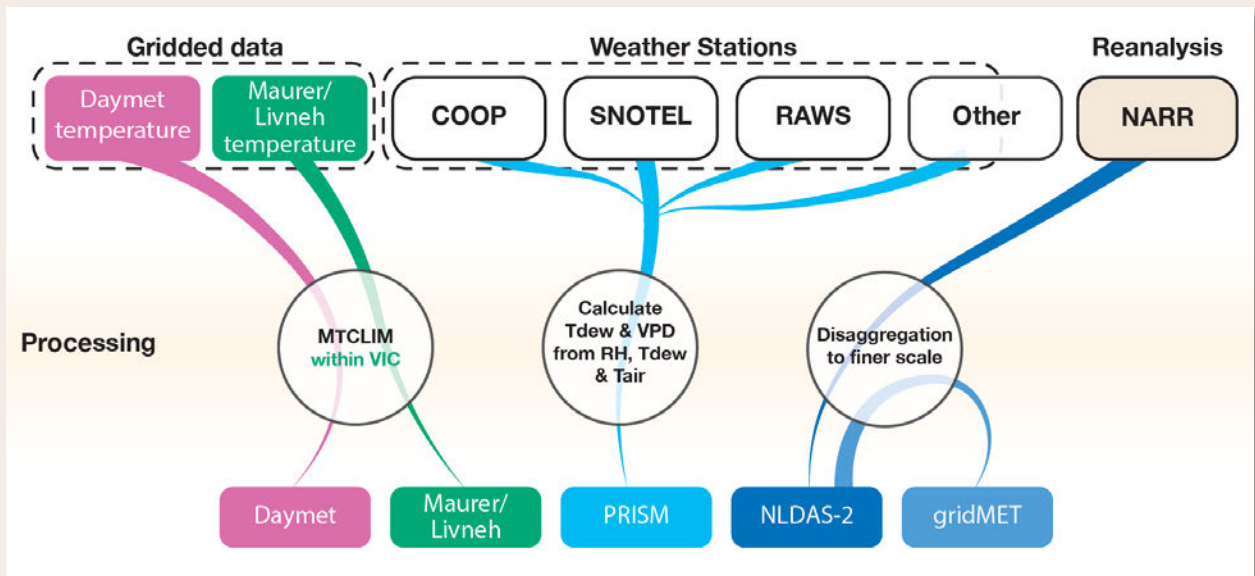


Figure 4.9

Flow diagram of the data sources and processes used to produce the high-resolution gridded humidity products featured here.

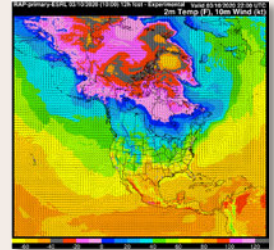
For the Upper Basin watersheds, which are generally snowmelt-dominated, real-time temperature and precipitation observations—the vast majority from SNOTEL stations—are used to directly produce the areal averages for forecast zones using station weightings determined through model calibration. The stations that are used have been pre-screened and vetted during the calibration process. Automated procedures identify potentially erroneous station values, which can be then manually corrected by forecasters. Freezing-level data from [Rapid Refresh](#), NOAA’s hourly operational weather reanalysis, is used to run the SNOW-17 model which types the precipitation as rain or snow. The data used for real-time operations and for calibration are very similar, with the calibration data having undergone additional quality control procedures.

For the Lower Basin watersheds, which are generally rainfall-dominated and respond more quickly to precipitation events, a denser station coverage is employed, with temperature and precipitation observations from multiple station networks, and then augmented by radar-based precipitation estimates to generate the real-time data. The radar data is most useful during the warm season when there is a larger radius of accurate information from the radar, due to reflection differences between rain and snow. The observations from all available stations are used, with no prior screening of stations, to create the highest possible station density. But the station temperature and precipitation values themselves are quality-controlled as in the Upper Basin. As in the Upper Basin, freezing-level data and SNOW-17 are used to type the precipitation into rain and snow. The real-time precipitation observations and radar precipitation estimates are transferred to a 4-km grid using an interpolation algorithm in the Multi-sensor Precipitation Estimate (MPE) software, the temperature observations are likewise transferred to a 4-km grid, and the grid cells within each forecast zone are then averaged to create the MAT and MAP data.

The historical calibration data for the Lower Basin are generated in a similar manner as the real-time data, except only the station precipitation data are used—not radar-based estimates—and a different algorithm and a finer grid (800-m) are used for the intermediate gridding step. The CBRFC has also generated a matching 800-m gridded historical dataset for the Upper Basin, but it is not used for operations or calibration at this time. Both of these intermediate 800-m gridded datasets can be made available to researchers.

In some respects, the real-time and historical meteorological forcings for the Colorado River Basin used by CBRFC can be considered to be of higher quality for hydrological modeling than many of the gridded datasets described earlier, since they are produced at higher resolution (at least during intermediate steps), use a greater number of stations, and use more rigorous quality control.

Rapid Refresh



Link:

<https://rapidrefresh.noaa.gov/>

The CBRFC recently worked with Utah State University to evaluate a physically based snow model that uses an energy balance to estimate snowpack processes, rather than just temperature and precipitation. Adoption of the potentially more accurate snow model, however, would require additional observational data that better characterized, at a minimum, surface radiation balance (P. Miller, pers. comm.). Due to the increased complexity of the energy balance model, real-time data may not be available for use within an operational framework. Increased model complexity may not necessarily yield more accurate results; for example, while radiation data are collected by a number of weather station networks focused on agricultural and water resource monitoring (Slater 2016), all but one of the gridded meteorological datasets discussed above that provide information on the surface radiation balance provide simulated—not observed—radiation fluxes (NLDAS-2 uses remotely sensed insolation).

4.4 Strengths and weaknesses of gridded data products

All gridded products that incorporate station data are likely to share common strengths and weaknesses related to those data. For example, any product that incorporates gage-measured precipitation—as do all of the datasets evaluated here—will display precipitation amounts that reflect undercatch (see Section 14.2) and therefore underestimate precipitation, particularly precipitation that falls as snow, unless some correction is applied, as in Newman et al. (2015). Because different areas may experience higher winds, receive a greater fraction of precipitation as snow, or use predominantly different styles of precipitation gage, the influence of undercatch may vary spatially.

The sparseness of observational data at high elevations—particularly prior to the late 1970s/early 1980s initiation of the SNOTEL and RAWS networks (Zachariassen et al. 2003; Schaefer and Paetzold 2001)—is another common weakness across all gridded data products. When and where the station network is sparse, there is greater opportunity for gridded datasets to differ as a result of other choices made in their development (e.g., lapse rate adjustment, interpolation method, etc.) (Walton and Hall 2018). Over the upper Colorado River Basin, this tends to lead to greater disagreement among datasets prior to the late 1970s and especially before the 1950s when there were generally fewer stations than in more recent decades (see Figure 4.7). There are also larger disagreements in areas with fewer weather stations, such as at higher elevations. For example, Henn et al. (2018) show greater absolute and relative differences between precipitation datasets at higher elevations in the Rocky Mountains. Figures in McAfee et al. (2019) suggest somewhat greater differences between datasets in temperature trends at higher elevations than trends at lower elevations, although there is some variability by month. However, the same paucity of high-elevation stations, and particularly high-elevation stations with long records, means that there is very limited ability to

evaluate gridded products or weather simulations against independent observations. This is especially problematic in the context of water resources, as the alpine regions are critical water supply areas within the Colorado River Basin (see Chapter 2).

As discussed above, choices about dataset construction are typically made so that the resulting data products are most appropriate for their intended purpose. As a result, different gridded data products have distinct characteristics. For example, TopoWx fills gaps and homogenizes data prior to gridding; as a result, temperature trends in TopoWx appear to be less variable in space than temperature trends in other products (see Figure 3 in Oyler et al. 2015). Because of limited station observations, it is difficult to determine whether spatially smooth gradients of trend or more spatially complex distributions of trend reflecting local variability in the sign and magnitude of trend represent actual changes. In the San Juan Mountains, temperature trends between 1990 and 2005 were similar at COOP and SNOTEL stations, despite the fact that the SNOTEL stations were, on average, located about 2580 feet higher in elevation than the COOP stations (Rangwala and Miller 2010), suggesting that trends may be more spatially consistent at least in some parts of the western U.S. While some data characteristics may seem consistent with the choices made in their construction or with known characteristics of the underlying station network or networks used, a new analysis and review by Newman, Clark, Longman, et al. (2019) highlights the fact that not all discrepancies between datasets are predictable based on their compilation. Some strengths and weaknesses of the datasets described in Tables 4.3 and 4.4 are listed in Table 4.5.

Table 4.5

Strengths and weaknesses associated with each of the gridded products described in Tables 4.3 and 4.4

Product Name	Strengths	Weaknesses
PRISM AN81d	Very high resolution (~0.5 mi, 800 m) daily product. Ability to capture cold-air pooling in many environments. Data available to near present (lag typically around 6 months).	Free daily product only available back to 1981.
PRISM AN81m and LT81m	Record extends back to 1895. Ability to capture cold-air pooling in many environments. Responsive to coastal, aspect, slope influence. Long history of use and well-known caveats. Data available to near present (lag typically around 6 months).	Temporally changing station network. There can be slight differences in values and spatial patterns with updates. More temporally stable data (LT81m) are not free.

Product Name	Strengths	Weaknesses
TopoWx	Very high spatial resolution (~0.5 mi, 800 m) daily data back to 1948. Homogenization and gap filling make data product potentially suitable for trend analysis. Incorporation of satellite data provides additional insight to spatial temperature patterns.	Only temperature is available. Homogenization could mask real spatial diversity in trends. There can be slight differences in values and spatial patterns with updates.
Livneh 2013/ Maurer 2002	Daily data available back to 1915 (1950 for Maurer). Internally consistent hydrometeorological variables simulated by VIC are provided.	Lapse rates may be too steep and temporally stable. It is unclear whether cold-air pooling can be evaluated—it may be possible in areas with particularly dense station coverage. There do not appear to be plans to update data past 2011. Precipitation is adjusted to PRISM, so spatial pattern will be similar to PRISM.
Livneh 2015	Daily data with coverage over Mexico and parts of Canada back to 1950. Internally consistent hydrometeorological variables are provided.	Lapse rates may be too steep. It is unclear whether or not cold-air pooling can be evaluated—it may be possible in areas with particularly dense station coverage. There do not appear to be plans to update data past 2013. Precipitation is adjusted to PRISM, so spatial pattern will be similar to PRISM.
gridMET	High-resolution (2.5 mi, 4 km) daily data with multiple variables suitable for ecological and fire weather modeling. Data are available in very near real time, but the last few days to weeks are based on the Climate Forecast System, rather than NLDAS-2.	Data are only available back to 1979. Variables other than temperature and precipitation are interpolated to 2.5mi (4 km), but are not adjusted for physiography at that scale, so variables may not be physically consistent. Precipitation and temperature are adjusted to PRISM, so spatial patterns will be similar to PRISM.
Hamlet 2005	Long-term temperature and precipitation trends are adjusted to match USHCN, so may be suitable for trend analysis. Daily data back to 1915.	Data are only available through 2003 and not specifically updated. Lapse rates may be too steep and static owing to fixed lapse rate. Precipitation is adjusted to PRISM, so spatial pattern will be similar to PRISM.
Hamlet 2010	Long-term temperature and precipitation trends are adjusted to match USHCN, so may be suitable for trend analysis. Daily data back to 1915.	Data are only available through 2010 and do not appear to be updated. Precipitation and temperature are

Product Name	Strengths	Weaknesses
		adjusted to PRISM, so spatial patterns will be similar to PRISM.
Daymet v. 3	Very high (~0.6 mi, 1 km) resolution daily data, with multiple variables suitable for ecological modeling. Data are updated frequently so data are available for very near present. Files of input station data for each grid cell are provided, so users can accurately identify stations used. Coverage for all of N. America	Data are only available back to 1980. Interpolation methods may not be able to capture very fine scale variability in precipitation.
Newman gridded ensembles	These provide multiple estimates of daily temperature and precipitation for each day for uncertainty quantification and can be used to explicitly predict the probability of precipitation occurrence.	The spatial resolution is relatively coarse. Data are only available through 2012 and update potential/schedule are unclear. Intended use requires a large amount of data.
nClimGrid (gridded data underlying the climate division data nClimDiv)	Monthly data are available back to 1895. Data are homogenized so may be suitable for trend analysis. Data are updated frequently. Spatio-temporal summaries, ranking, etc., are readily available through Climate at a Glance.	This is a relatively new product; caveats associated with the data are not yet well defined.
NLDAS-2	Sub-daily records for a full suite of meteorological variables are available. Data are available for close to present.	The spatial resolution is relatively coarse. Data are interpolated reanalysis, which are relatively prone to error. Behnke et al. (2016) note NLDAS-2 has some of the highest errors relative to station observations.

For users with particular needs, there may be relatively little choice in which data product to use. Applications that require spatially continuous hourly data are limited to NLDAS-2 of the datasets evaluated here. In other cases, there may appear to be greater choice, but apparently different products may be very similar. Only the Maurer et al. (2002), Livneh et al. (2013 and 2015), Hamlet and Lettenmaier (2005), and Deems and Hamlet (2010) products provide daily precipitation data that extend back prior to the early 1980s or late 1970s. These five products differ very little from each other in underlying data or construction methodology. All are based exclusively on COOP data in the U.S., although there are some differences in which specific stations were used (Hamlet and Lettenmaier 2005). All except Hamlet 2010 (Deems and Hamlet 2010) use pre-defined temperature lapse rates (-3.6°F/1000 feet [-6.5°C/km] or -3.3°F/1000 feet [-6.1°C/km]) that are, at least for minimum temperature, steeper over the Upper Basin

than observed in other data products (McAfee et al. 2019; Newman et al. 2015). Hamlet (2010) scales temperature to the PRISM climatology (Deems and Hamlet 2010). All of the products adjust precipitation patterns to the PRISM climatology, although they use different normal periods. All employ the same SYMAP interpolation. The primary differences between these products are that 1) they are supplied over different time periods and domains at different spatial resolutions, 2) the Hamlet (2005 and 2010) method homogenizes station data prior to interpolation, which the Maurer and Livneh methods do not (Maurer et al. 2002; Livneh et al. 2013; 2015; Hamlet and Lettenmaier 2005; Deems and Hamlet 2010), and 3) they adjust their precipitation to different PRISM precipitation climatologies—1961–1990 for most vs. 1981–2010 for Livneh et al. (2015)—that display slightly different spatial patterns in precipitation.

4.5 Considerations in the analysis of gridded data products

Many of the characteristics of station and gridded data products discussed above imply certain limitations in their analysis. As noted by Newman et al. (2019), choices about which data to include, and particularly the density of input data, can have a significant influence on the effective resolution of the data. For example, a nominally high-resolution product based on a small number of stations may not be able to accurately reflect fine-scale spatial patterns, especially in complex terrain, such as in the Colorado River Basin. Users should also be aware that gridded products do not reflect variability that occurs at finer scales than their nominal resolution. For example, a product with 2.5 x 2.5 mi resolution will reflect the average temperature over 6.25 square miles, but local temperatures may vary substantially within that area. Likewise, a daily precipitation total does not imply information about when during the day precipitation fell or how heavy it was. A final consideration most pertinent to daily data is that different stations may use different start and end times for their day (e.g., 9:00 a.m. vs. local midnight vs. 0:00 UTC), and those may change over time, so a given day may not cover the exact same period of time (see (Menne et al. 2012; Leeper, Rennie, and Palecki 2015).

Intercomparison

The first consideration is related to dataset intercomparison. Because different datasets are developed using different methods, disagreement in poorly observed areas may be expected (Walton and Hall 2018). Shared underlying station data can and should lead to agreement in areas where the station network is densest, so agreement between datasets in those areas or between specific grid cells and stations in those grid cells that contribute to the gridded product may not be effective measures of similarity or quality (Daly 2006). For example, Behnke et al. (2016) find the Livneh et al. (2013) and Maurer et al. (2002) datasets, which use only COOP

stations, to have relatively small biases in mean precipitation and maximum temperature, but they compare the gridded dataset to a set of weather stations that is likely dominated by COOP stations because of the chosen time period (1981–2010) and data completeness criteria. Station siting may also influence the representativeness of gridded products. Physiographic features that are not well sampled in the observational network may not be accurately portrayed in even the most complex and highest resolution gridded products. For example, Strachan and Daly (2017) found that systematic undersampling of mid-slope locations in the Great Basin drove biases in the representation of temperature patterns in PRISM, even at very high spatial resolutions. Gutmann et al. (2012) found that leeward precipitation amounts were overestimated in PRISM in parts of southwestern Colorado where there were few weather stations on leeward slopes.

It is also important to be aware of interdependence between datasets beyond shared underlying data, so that agreement between those products is not over-interpreted in terms of confidence. Adjusting precipitation patterns in gridded datasets to match the PRISM climatology is very common, as is application of a pre-determined static lapse rate for both minimum and maximum temperatures (Figure 4.5). Even homogenization practices are very similar. TopoWx (Oyler, Ballantyne, et al. 2015) and nClimGrid (Vose et al. 2014) both use the pairwise comparison method described in Menne and Williams (2009), and Hamlet homogenizes station data to USHCN records, which are homogenized using the Menne and Williams (2009) pairwise method.

Analysis of trends

The second major consideration is related to the analysis of trends. Ideally, trend analysis should only be performed on data that are known to be free from inhomogeneities. As a result, many producers of gridded data caution against the use of their data for trend analysis. Redundancy in the input data might make it less likely that gridded data will display inhomogeneities particular to an individual station—for example, due to a station move (Groisman and Easterling 1994). In areas with few stations, however, inhomogeneities in individual stations, or the loss of an individual station, may be reflected in gridded products (McAfee, Guentchev, and Eischeid 2014). Inhomogeneities that impact an entire station network are often reflected in gridded data (Groisman and Easterling 1994; Oyler, Dobrowski, et al. 2015). Adding data from new station networks preferentially located in different kinds of locations or using different instrumentation than existing stations can also induce inhomogeneities in gridded data (McAfee et al. 2019) even when steps have been taken to mitigate the impact. Known network-wide or common spatially extensive causes of inhomogeneity in the region include changes in the time of observation (Karl et al. 1986) and instrumentation (Quayle et al. 1991) at COOP sites, urbanization (Karl, Diaz,

and Kukla 1988; Hausfather et al. 2013), changes in instrumentation at SNOTEL sites (Oyler, Ballantyne, et al. 2015), and introduction of new station networks (McAfee et al. 2019). Even the PRISM LT81m dataset, which includes only longer-duration station networks, is not recommended for trend analysis (PRISM 2016). Of the data products evaluated here, only nClimGrid, TopoWx, and the Hamlet products are homogenized in a way that may make them suitable for trend analysis (Oyler, Ballantyne, et al. 2015; Oyler et al. 2016; Hamlet and Lettenmaier 2005; Deems and Hamlet 2010; Vose et al. 2014; Walton and Hall 2018). Gap-filling and homogenization, however, could mask real spatial variability in trends, so homogenized data may be more appropriate for characterizing regional trends than highly local ones. The effects of homogenization can be seen in the precipitation trend maps shown in Henn et al. (2018) Figure 7. The trend patterns in the homogenized Hamlet et al. 2010 data (Deems and Hamlet 2010) are spatially smoother than in the other products evaluated. The trend maps shown in Henn et al. (2018) also demonstrate that while major features of the 1982-2006 trend patterns are replicated—reductions in precipitation over the Lower Colorado Basin and increasing precipitation over California—there are localized differences in trend patterns and magnitudes over parts of the Upper Colorado Basin.

Because of the complex ways in which choices about data selection, adjustment, and interpolation combine (Newman et al. 2019), it may be impossible to know whether gridded data contain detectable inhomogeneities without thorough statistical investigation. Guentchev, Barsugli, and Eischeid (2010) analyzed precipitation from the Maurer, BL (which is similar in construction to the Maurer data, but uses different stations and is not described Table 4.4), and PRISM datasets over the full Colorado River Basin for the second half of the 20th century. PRISM had the highest percent of grid cells without detectable inhomogeneities (88%), followed by Maurer (83%) and BL (77%). While all of the datasets were generally free of inhomogeneities, the inhomogeneities that exist were in the same places in all datasets. They tended to be clustered in specific, largely high-elevation sub-basins in the Lower Basin: the Little Colorado, the Lower Colorado-Lake Mead, and the Upper Gila. Repeating this type of analysis for the increased selection of temperature and precipitation data that are available now, as well as for specific time periods, would be beneficial and would help researchers in the region identify datasets that might be suitable for climate trend analysis or for use in hydrologic models whose output will be analyzed for long-term variability.

4.6 Considerations in gridded data product selection

The single most important thing to know about selecting a gridded data product is that there is no perfect product—if there were perfect observations for every point, there would still be “errors” in all of the gridded products. For example, Gutmann et al. (2012) note that gridded precipitation from the Weather Research and Forecasting Model (WRF) and the 1971–2000 PRISM climatology predict different amounts of precipitation spillover from the windward to leeward side in parts of the San Juan Mountains. This is an area that did not have good leeside station coverage until recently; data from one station installed in late 2008 suggest that WRF was providing more accurate precipitation totals. Nor is there a best product, although there might be a best choice for certain applications. Data selection is necessarily based on both practical and scientific considerations. Many of the considerations that go into choosing a historical gridded climate data product are similar to those that might be used in climate change evaluation. In-depth discussion of the topic is provided by Vano et al. (2018) and Daly (2006), but some practical and scientific guidance for data selection is briefly outlined here.

Practical considerations

From a practical standpoint, a user might reasonably consider eight criteria about data products in choosing which to use. Many of the practical considerations are easily assessed with basic product metadata.

1. Does the data product supply the weather or climate variables necessary for the application? Some analyses or modeling efforts may require a single variable, while others might require a much more extensive suite of variables. It is often easier to use multiple variables from a single gridded product because they are likely to be provided on the same grid, minimizing geospatial processing.
2. Does the data product provide data with the appropriate temporal coverage? Specific considerations related to temporal coverage include the length of the dataset, how frequently it is updated, and latency—the lag in data availability relative to real-time. There may also be concerns related to how new data are released. Some data products, such as TopoWx, may release updates with new versions of historical data and, thus, may not be directly comparable to previous versions (although the two versions of TopoWx shown here are essentially identical over the Upper Basin). In this case, updating the data product may require downloading an entirely new database for the full period. Others, such as gridMET, simply extend the length of the data product during most updates.
3. Does the data product provide data at the appropriate temporal frequency? Monthly data are somewhat more widely available than daily

data, which are, in turn, much more common than sub-daily data—at least at high spatial resolution.

4. Does the data product cover the necessary spatial domain? For applications entirely within the Colorado River Basin, this is not often of concern. Most products provide reasonable coverage over the contiguous United States. However, applications that include transnational river basins (e.g., Rio Grande, Columbia), may require data to be consistent across national boundaries, and such data products are less common.
5. Is the data product at the appropriate spatial resolution? Questions about spatial resolution may be practical—a model operates at $X \text{ mi}^2$ resolution and requires input data at that resolution—or scientific—the process in question occurs at $Y \text{ mi}^2$ scale and cannot be detected in coarser data. Conversely, the spatial resolution of a data product will also influence computational time and storage demands, so data that are too finely scaled may be inconvenient.
6. What resources are required to use the data? Although many data products are served free of cost, some data (e.g., PRISM LT81m) are only available for purchase. The decision to use a product that is not free would be contingent on funding and potentially on the user's ability to justify the cost to a funder. Resource issues related to file conversion—for example, from GRIB to GeoTiff for model compatibility—data storage or other processing steps could also influence the choice of dataset.
7. Is it necessary to assess uncertainty, use multiple scenarios, or identify a single type of scenario? Only the Newman et al. 2015 dataset is explicitly designed to provide uncertainty quantification. However, it may be possible to include multiple datasets with input data and development techniques that are as different as possible. Related considerations may include whether specific datasets seem to routinely provide “best case” (e.g., robust average flows, modest flood peaks), middle-of-the-road, or “worst case” (e.g., lower total flow, high flood peaks) outcomes and which of those is most appropriate for the decision at hand.
8. Are there any other practical considerations? There may be questions about whether a model being used has been parameterized with a specific climate dataset and whether there are consistency issues that need to be considered—for example, a desire to compare results from a new study with a previous one that would be simplified by using the same climate data.

Scientific considerations

There are also scientific considerations related to dataset choice. Unlike the practical decisions, however, consideration of the scientific characteristics of data typically require a more in-depth knowledge of the data product. Daly (2006) provides a discussion around dataset choice in relation to physiographic features, along with background information on how common interpolation techniques handle physiography. Scientific considerations may apply particularly in post-hoc analysis of the results, in assessing the confidence and uncertainty around certain statements, as well as in gauging how widely the results could be applied to other regions, systems, or time periods.

1. Is the effective resolution of the grid cell consistent with its nominal or apparent resolution? As computational capacity has improved, it has become possible to interpolate climate data to a very fine apparent resolution, even though little to no new information has been incorporated. For example, gridded data with a nominally high spatial resolution that rely on a low-density station network may have a lower effective than apparent resolution (Newman et al. 2019). The gridMET process adds additional climate-relevant information to NLDAS-2-derived temperature, precipitation, and humidity, but simply interpolates winds and radiation, so the effective resolution of gridMET wind and radiation are the NLDAS-2 resolution, not their nominal ~2.5-mi resolution (Abatzoglou 2013).
2. Do data need to be internally physically consistent? In some cases, detailed process modeling may require suites of variables that are physically consistent. For example, some applications need data that can accurately reflect a drop in temperatures caused by evaporation or melting of precipitation in order to better forecast precipitation amount, intensity, and whether it will fall as rain, snow, or freezing precipitation (e.g., Barros and Lettenmaier 1994; Kain, Goss, and Baldwin 2000). The ARkStorm@Tahoe project—which simulated snowfall and flooding caused by a single significant storm event to evaluate environmental and socio-economic impacts and real-time response mechanisms—required such a complex data set in order to develop realistic and accurate timelines and spatial maps of flooding and related hazards in a topographically complex region (Albano et al. 2016). Producing such data typically requires dynamical generation or downscaling (e.g., Gutmann et al. 2012). Most observationally based gridded data products probably cannot provide this level of internal consistency, but it is also not clear how many applications would require this.
3. How might known data characteristics influence an application? Data intercomparisons, such as (Behnke et al. 2016; Henn et al. 2018; Walton

and Hall 2018) and many others evaluate whether certain datasets are relatively cool or warm, or wet or dry in certain locations, and data documentation often highlights known errors, strengths and weaknesses in data products. However, it can be difficult to determine which data are most correct, either because station data are lacking, and there is no real ground-truth, or because the available station data were used to produce the gridded data and do not provide an independent check (Daly 2006). More detailed studies might be required to understand which datasets are more accurate and why. There is also the question of how much errors or biases impact any given application. For example, Strachan and Daly (2017) found that cool biases in PRISM, related to the siting of available input stations, impacted growing-degree day calculations more than they influenced assessment of the length of the frost-free season or temperature-based estimates of the percent of precipitation falling as snow. In that case, users analyzing growing degree days might be particularly cautious about their subsequent interpretations and conclusions.

4. Is it appropriate to use records with particular types of inhomogeneities? Data containing inhomogeneities that impact only how climate is recorded (e.g., inhomogeneities related to changes in instrumentation) are likely to be problematic in many applications and can lead to misleading conclusions (e.g., Oyler, Dobrowski, et al. 2015). But inhomogeneities related to land cover change, such as urbanization, (Karl, Diaz, and Kukla 1988) may be valuable components of data for some applications. Identifying and correctly quantifying trends related to large-scale forcing, such as global warming, requires removing both sudden and “creeping” inhomogeneities (Menne and Williams 2009). Understanding local-scale changes in evaporative demand, however, might require climate records that reflect the sum of all changes, including any local warming related to land-cover change due to urbanization, conversion to agriculture, etc. In such cases, homogenized data may, in fact, be inappropriate.

In sum, both practical and scientific considerations should influence users' choices about which data product to use. The effect that those choices might have on subsequent analyses is often not well characterized. There are a number of open questions about weather and climate in complex topography, how weather and climate variability across large basins influences hydrology, and about how best to use imperfect gridded climate data to better understand natural and managed hydrologic systems. Research efforts to address these questions are on-going. For the time being, users of these products should attempt to assess basic information about the gridded or station data they use and consider how the characteristics of those data might influence their analysis.

4.7 Challenges and opportunities

Challenge

While commonly used gridded climate datasets show very similar variability and trends in precipitation and temperature for the basin, disagreements between the datasets are larger for the sparsely instrumented high-elevation areas in the Upper Basin—the areas that generate the vast majority of the basin’s runoff.

Opportunities

- Use other types of measurements, such as streamflow and radar, to constrain the gridded estimates of temperature and precipitation, and add novel observation techniques (e.g., Airborne Snow Observatory; see Chapter 5) to bolster ongoing observations.
- Use numerical weather prediction models (Chapter 7) for spatiotemporal interpolation and validation of observation-based products.

Challenge

It is increasingly understood that the gridded climate datasets have inherent uncertainties and differ from each other, but how those uncertainties and differences manifest in the outputs of typical hydroclimate modeling and analysis tasks needs to be better explored and communicated to users.

Opportunities

- Conduct formal intercomparisons between gridded datasets in the context of specific applications and outputs (e.g., Alder and Hostetler 2019 on the use of different gridded climate datasets for statistical downscaling of GCM data; Chapter 11).
- Application projects can consider including a testing phase in which multiple gridded datasets are tested on a limited portion of the project’s domain or analyses.
- Both researchers and users can acknowledge that all data are imperfect, and move away from trying to identify a single “best” product toward greater consideration of the data characteristics that are, and are not, important for their questions and analyses.



Chapter 5

Observations—Hydrology

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Key points

- Robust real-time observations and long-term records of snowpack, streamflow, soil moisture, and other hydrologic variables are key inputs to basin streamflow forecasting and system modeling.
- Point measurements of these variables are not dense enough to fully represent spatial variability across the basin, and not necessarily sited to optimally inform streamflow forecasts.
- For snowpack observations, the in situ SNOTEL network has limitations but remains essential to monitoring and skillful streamflow forecasting.
- Spatially distributed snowpack data from models and remote sensing are increasingly used to augment SNOTEL data, though most of these sources depend on SNOTEL data for calibration.
- Accurate and useful streamflow inputs depend on both the robustness of the gage network and the procedures used to adjust and naturalize gaged streamflows to account for human activity.
- Flow naturalization methods try to estimate what the streamflow at a gage would have been, or will be, without the impacts of upstream human activity; naturalization methods vary from agency to agency, depending on the time scale and application.
- Evaporation and evapotranspiration estimates are central to flow naturalization, thus as more types of observations become available, models used to calculate these variables are being refined in both physical process modeling and input data used.
- In situ measurements of soil moisture and evaporation-related variables are especially sparse, and spatially distributed data from models and remote sensing have a larger role to play in condition monitoring and streamflow forecasting.
- Realizing the full value of spatially distributed hydrologic data will ultimately require streamflow-forecasting and system-modeling frameworks that are explicitly designed to use those data as inputs.

5.1 Overview

Robust real-time observations and long-term records of snowpack, streamflow, soil moisture, and other hydrologic variables are critical to multiple components of system modeling in the basin, at all timescales. Many of these observations are used as real-time inputs to the CBRFC streamflow forecast models (Chapter 8) and Reclamation system models (Chapter 3), while long-term records are used to calibrate the models. The long-term records are used to evaluate long-term hydrologic trends and their causes (Chapter 2), and also serve as the historical planning baseline (Chapter 9) for evaluating potential future risk. They are further used to calibrate and validate alternative planning hydrologies based on tree rings (Chapter 10) and climate model output (Chapter 11).

Ideally, all observations of hydrologic variables would have long periods of record, be consistent over time (temporally homogeneous), and be spatially dense enough across large basins that the observing sites were representative of all areas in between sites. All observed records fall short of one or more of these ideal characteristics, and it is important to understand the strengths and weaknesses of different datasets relative to the intended application. Often, there are inherent tradeoffs among these ideal characteristics. For example, many satellite-based observations have high spatial density (resolution of 1 km or less), but few of these datasets extend before 2000.

5.2 Snowpack observations and monitoring

The discussion of hydrology observations begins with snowpack observations because most of the annual water supply in the basin likewise begins as snowpack (Chapter 2). The snowpack is a key interface between meteorological processes (weather and climate) and hydrological processes. The physical characteristics of the snowpack are controlled by weather and climate through the accumulation of precipitation occurring as snowfall, redistribution by wind, sublimation losses, and melt driven by solar and longwave radiation, sensible heat (i.e., measured as temperature), and latent heat (from water phase-change).

The interactions of all these processes with complex terrain and vegetation means that the snowpack is a highly dynamic entity in space and in time. Some characteristics of the spatial patterns and temporal patterns of the snowpack are fairly consistent from year to year; e.g., more snow accumulates earlier and throughout the season, and persists later in the spring, at higher elevations and on north-facing exposures. However, the details of these patterns can vary greatly from year to year and from basin to basin, influencing the magnitude and timing of snowmelt-driven runoff. Inadequate characterization of these details of the snowpack is a significant source of error in seasonal runoff forecasting, though a smaller source than the uncertainty in future precipitation and temperature (Chapter 8).

The most important characteristic of the snowpack from the standpoint of monitoring and forecasting water supply is snow water equivalent (SWE). SWE can be measured directly through in situ observations, modeled from precipitation observations and other meteorological data, or derived from measurements of snow depth and estimates of snow density, since SWE is the product of those two terms. Snow depth is much more spatially variable than snow density, and so snow depth is by far the larger contributor to the spatial and temporal variation in SWE.

Table 5.1 summarizes key characteristics of the principal snowpack data networks and products that are used or consulted by water management entities in the Colorado River Basin; these sources are further described in the following text. This list is not intended to be comprehensive; other data and networks may also be used in the basin.

Table 5.1

Snowpack monitoring networks, data, and products available for some or all of the Colorado River Basin and used by water management agencies. See the text for further description of these networks/products.

Network or Product	Method	Variables	Spatial Resolution or # Stations	Spatial Coverage	Temporal Resolution
SNOTEL (NRCS)	In situ measurement	SWE, snow depth, precipitation, many other weather obs.	>175 stations in basin; ~900 West-wide	West-wide	Hourly or 3-hourly
Snow course (NRCS)	In situ measurement	SWE, snow depth, snow density	82 courses in the basin	West-wide	Monthly or semi-monthly
Snow-17 snow model (CBRFC)	Temperature-index snow accumulation and ablation model, which uses area-averaged precipitation data derived from point observations, plus freezing-level data	SWE, snow covered area	~600 modeling units in the basin	CBRFC domain (CRB + E. Great Basin)	Daily
MODSCAG (NASA JPL)	MODIS satellite imagery used to derive snow extent and properties	Fractional snow-covered area, snow grain size	~500 km	CONUS	Daily, 2-4 day lag
MODDRFS (NASA JPL)	MODIS satellite imagery used to derive snow properties	Radiative melt forcing	~500 km	North and South America	Daily, 2-4 day lag

Network or Product	Method	Variables	Spatial Resolution or # Stations	Spatial Coverage	Temporal Resolution
ASO (NASA JPL)	Airborne-LiDAR-measured snow depth, combined with snow density (modeled or measured)	SWE, snow depth (also snow albedo from separate sensor)	50 m	As flights are made on demand; currently mostly in CA, some in CO	As flights are made on demand; typically 1-6 per season per watershed
SNODAS (NOAA NOHRSC)	Process-based snow model which assimilates satellite, airborne, and in situ snow data and weather obs	SWE, snow depth, snowmelt, sublimation, snow temperature	1 km	CONUS	Daily
MODIS-based spatial estimates (Univ. of Colorado)	Statistical regression model based on in situ SWE, MODSCAG, physiographic variables, energy-balance snow model	SWE, snow cover	500 m	California; Southern Rockies inc. UCRB; Northern Rockies	Typically biweekly, 3-5 day lag
SWANN/SnowView (Univ. of Arizona)	Process-based snow model and neural network algorithm, uses SNOTEL SWE and MODIS SCA	SWE, snow cover	1 km	CONUS	Daily

In situ snowpack observations: SNOTEL and snow courses

For over 80 years, snowpack monitoring and water supply forecasting throughout the western U.S. has relied on a network of in situ ground-based observations managed and maintained by the Natural Resources Conservation Service (NRCS) along with many state and local cooperators. From the mid-1930s until the late 1970s, these observations came solely from snow courses that were manually measured monthly or semi-monthly (Figure 5.1).



Figure 5.1

Soil Conservation Service (SCS) snow surveyors measuring a snow course in the 1940s. The SCS is now the Natural Resources Conservation Service (NRCS). (Source: Helms, Phillips, and Reich 2008)

Starting in the late 1970s, the snow courses were increasingly augmented by, and at many sites replaced by, automated SNOTEL (SNOWpack TELElemetry) stations that report SWE, snow depth, precipitation, temperature, and other variables on an hourly or 3-hourly basis, greatly enhancing the timeliness and temporal resolution of snowpack data relative to manually measured snow courses. Currently, there are 196 SNOTEL sites that are within or near to (<10 km) the boundaries of the Upper Basin, and 46 for the Lower Basin (Figure 5.2). Monthly manual SWE measurements are still taken at 104 snow courses in the Upper Basin, mainly in Colorado, and 36 snow courses in the Lower Basin ([NRCS website](#)).

Several years ago, NRCS implemented an Interactive Map to provide real-time map-based access to primary data from all SNOTEL and snow-course sites (SWE, snow depth, and precipitation) as well as many calculated parameters such as SWE % of median, change in SWE, and snow density. The map also shows soil moisture data from SNOTEL and SCAN sites, observed and forecasted streamflows, forecast verification statistics, and reservoir storage. The Interactive Map is routinely enhanced (now in Version 5.0) and has rapidly become a highly valuable tool for snowpack monitoring and other hydrologic monitoring.

NRCS Interactive Map



Link:

<https://www.nrcs.usda.gov/wps/portal/wcc/home/quicklinks/predefinedMaps/>

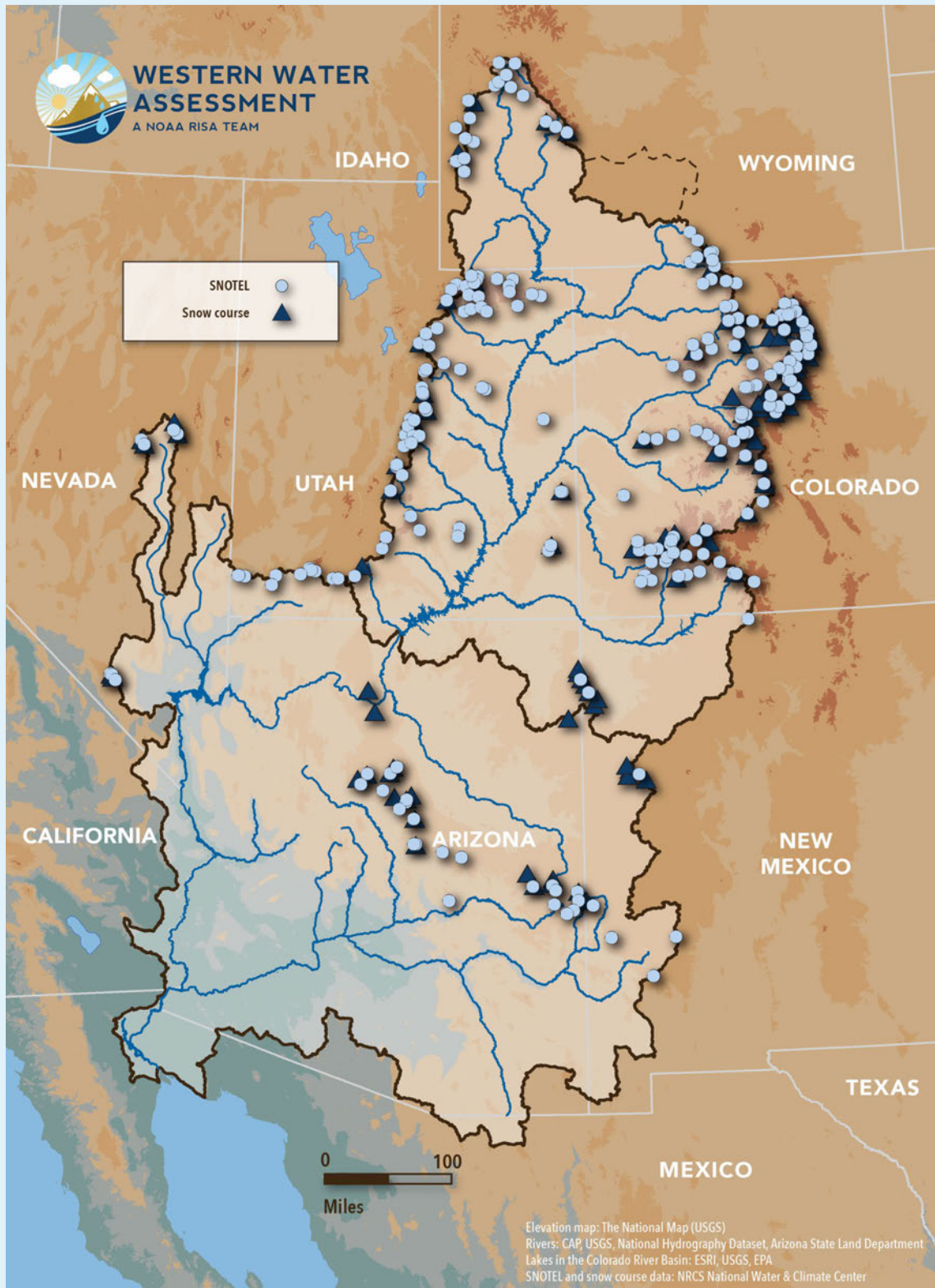


Figure 5.2

Locations of active SNOTEL sites and snow courses in the Colorado River Basin.

The snow-course and SNOTEL network in the western U.S. has been developed by NRCS to support their seasonal water supply forecasts, as well as for general snow monitoring. Thus, the characteristics of the network have influenced the NRCS water-supply forecasting approach, and vice versa. In that approach, which has been used and refined for several decades, statistical modeling (currently, principal components regression) is used to relate several predictors—typically water-year-to-date precipitation and current SWE from SNOTEL sites—to the target predicted value: spring-summer streamflow at a given forecast point. The model is calibrated on historical data, and then for forecasting, the model equation is applied to real-time predictor data. Point-based in situ measurements are well suited for such an approach that uses a limited number of predictors to represent the basin snowpack above the stream gage being forecasted. Additional details of the NRCS statistical forecasting approach are provided in Chapter 8.

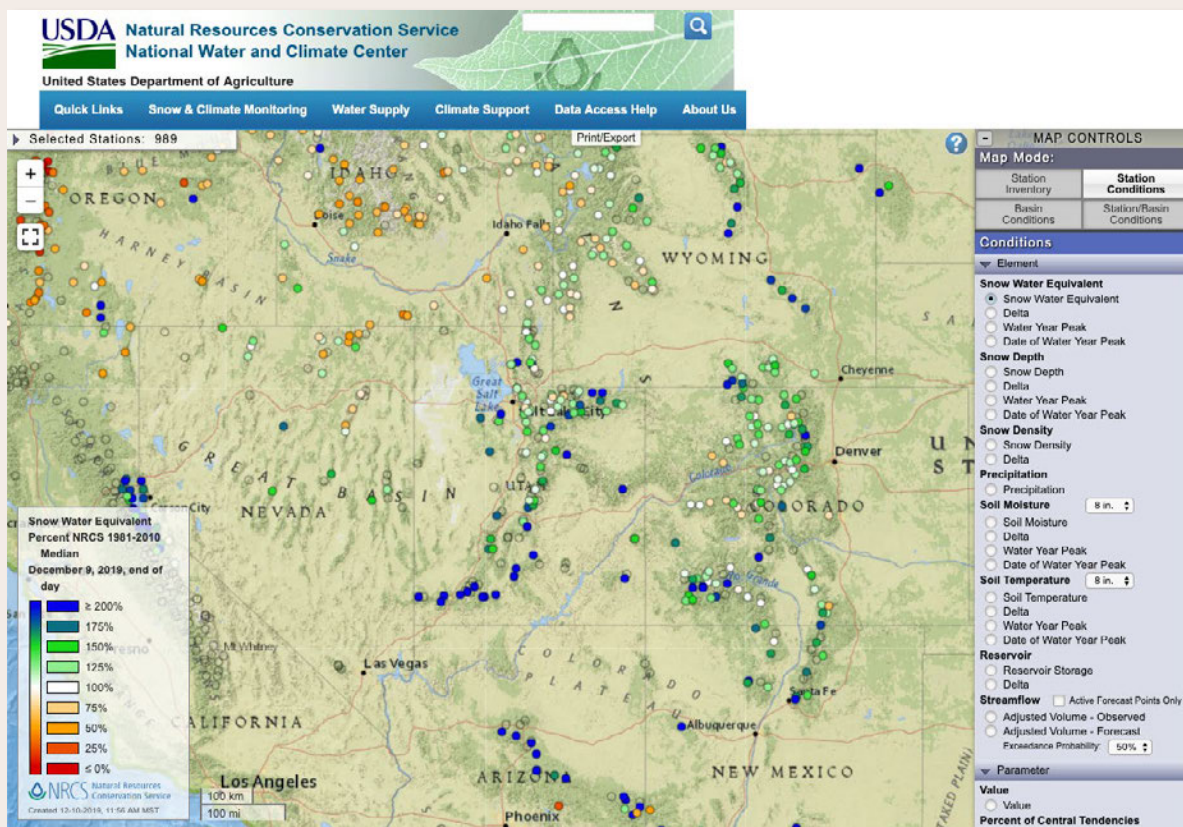


Figure 5.3

The NRCS Interactive Map (Version 5.0) provides real-time access to SNOTEL and snow-course data, as well as observed and forecasted streamflows. (Source: NRCS; <https://www.nrcs.usda.gov/wps/portal/wcc/home/quicklinks/predefinedMaps/>)

The observations from the SNOTEL/snow-course network in most years and locations provide reliable indications of snowpack conditions in the Colorado River Basin and its sub-basins, as indicated by the high overall skill of April 1 water supply forecasts that are based solely on those observations. For example, at key Upper Basin forecast points such as Yampa near Maybell, Gunnison near Grand Junction, and Colorado near Cameo, the explained variance of NRCS April 1 forecasted April-July streamflow is $R^2 = 0.63\text{--}0.80$ (G. Goodbody, NRCS, pers. comm.).

SNOTEL sites provide very accurate *point* measurements that can, to a large degree, collectively represent the vast majority of a basin that is not being directly measured. However, there are general limitations in network coverage; due to siting constraints and considerations, SNOTEL sites are not located above treeline, on steeper slopes and southerly aspects, or at lower elevations where snowpack is generally low or intermittent. Thus in years with anomalous spatial patterns, such as much reduced wind scour and sublimation loss above treeline, or unusually high mid-winter melt on south-facing slopes, or unusually high accumulation at lower elevations relative to higher elevations, the SNOTELs and snow courses will not capture the actual basin-wide SWE conditions as well as in a more typical year. Also, some watersheds have relatively fewer SNOTEL and snow course sites, or lack in situ sites completely. According to the CBRFC, it is likely that there is greater forecast error related to snowpack conditions in these data-sparse areas, though no quantitative analysis has been done to confirm this (FROMUS report, Reclamation and Colorado Basin River Forecast Center in preparation).

Every year, several new SNOTEL sites are added to the network in the basin, and the network is expanding, though slowly. A more concerted effort to add SNOTEL sites in relatively data-poor basins could eventually reduce snow-related uncertainty in runoff forecasts, though the return on investment would be slow, since 10–15 years of record are needed to adequately calibrate data from new SNOTEL sites in the CBRFC forecast model (Reclamation and Colorado Basin River Forecast Center in preparation), as well as the NRCS forecast model.

Over time, the instrumentation at SNOTEL sites has been updated and additional sensors have been added, notably for soil moisture. Continued modernization and upgrading would ideally include more sensors, including image capture that could effectively extend the spatial reach of each site.

Despite some limitations, the point SWE observations from SNOTEL and snow courses continue to serve as the basis for skillful statistical forecasts of seasonal streamflows for the Colorado River Basin. However, the physical models also used to forecast runoff (e.g., CBRFC's primary forecast system) require additional modeling of the snowpack that directly addresses the

issue of spatial representativeness, as well as additional input data, as detailed below. The more spatially explicit depiction of snowpack that results can also add value for general snow monitoring.

Other in situ snow observations

While the SNOTEL and snow course SWE observations are the backbone of snowpack monitoring, there are additional in situ snow observations that help round out the picture of the snowpack, especially at lower elevations. Most stations in the COOP weather observer network (Chapter 4) report daily snowfall and snow depth on the ground, in addition to temperature and precipitation. For example, on a typical day in March 2019, 40 of 56 COOP observers in western Colorado reported snowfall and snow depth. SWE on the ground can be estimated from snow depth using measurements of, or assumptions about, snow density.

Since its initiation in 1997, the CoCoRaHS network has become an important supplemental source of precipitation data for weather and climate monitoring and other purposes (Reges et al. 2016). The volunteer observers who make up the CoCoRaHS network are encouraged to record snow measurements along with their daily precipitation observations, including snowfall, daily SWE accumulation, snow depth, and total SWE on the ground. Most CoCoRaHS observers do record snowfall and the daily SWE accumulation, and most of those also record snow depth, though far fewer of them measure and record total SWE. For example, on the same day in March 2019, roughly 100 CoCoRaHS observers across the Upper Basin (mainly in western Colorado) reported snow depth, and roughly 20 of them also reported total SWE. Both COOP and CoCoRaHS snow observations are now being incorporated into the NOAA SNODAS products, as described below, while CoCoRaHS data are incorporated into the MODIS-based spatial estimates of SWE from the University of Colorado, also described below.

Remote sensing of snow

Remote sensing from satellite or airborne platforms provides spatially continuous data that can usefully complement the point SWE data from SNOTEL or other in situ observations. In the Colorado River Basin, remotely sensed snow data is being increasingly deployed and integrated into snowpack monitoring and runoff forecasting systems. It is important to note that remote sensing products have inherent uncertainties not shared by in situ measurements. They *infer* the variable of interest (e.g., fractional snow cover), typically by translating a different variable being sensed (e.g., reflected light from the surface at certain wavelengths) by way of an algorithm. In general, airborne products are more reliable than satellite products, mainly due to the sensor being roughly 2-3 orders of magnitude closer to the land surface.

CoCoRaHS Network



Link:
<https://www.cocorahs.org>

MODIS, MODSCAG and MODDRFS

MODIS is a moderate-resolution (500 m for most products) multi-spectral sensor that is currently on two different satellites, Aqua and Terra, with daily near-global coverage, with data availability back to 2000. NASA JPL developed, and continues to refine, two snow-specific data products from MODIS that are made available in near real-time: one that depicts fractional snow-covered-area and snow-grain size (MODSCAG) and one that depicts the radiative melt forcing from dust-on-snow (MODDRFS) (Painter et al. 2009). While MODSCAG does not capture SWE, it can be integrated with in situ observations in a snow-modeling environment to better represent the distribution of SWE across a landscape. See Figure 8.4 (in Chapter 8) for examples of MODSCAG and MODDRFS applications in the Colorado River Basin.

Data from MODIS have been used both qualitatively and quantitatively by the CBRFC to inform streamflow forecasting since 2013 (Bryant et al. 2013). The MODSCAG data on fractional snow-covered area is used qualitatively to manually adjust forecasts, though the CBRFC is working with NASA JPL to develop a dataset that would allow for quantitative information to be used in operational streamflow forecasting. The MODDRFS information regarding changes to snow albedo due to dust-on-snow is quantitatively used to assess the impact of dust on snow to snowmelt runoff, and adjust the CBRFC snow model to compensate. The snow model used by the CBRFC (as described below) is not able to directly use spatially distributed data as input so their hydrologists have had to work around this limitation.

Airborne Snow Observatory (ASO)

The Airborne Snow Observatory (ASO) is an airplane-based platform developed by NASA JPL in 2013 (Painter et al. 2016). It carries a very high-resolution scanning LiDAR (Light Detection and Ranging) sensor that can very accurately measure snow depth as the difference between the current snow-surface height and the land-surface height measured earlier during snow-free conditions. Observed or modeled snow density, or both, is then used to translate the snow-depth data into SWE, resulting in a spatial SWE product with a 50-m resolution (Figure 5.4). A second sensor, an imaging spectrometer, measures snow albedo and thus the radiative melt forcing from dust-on-snow. ASO data are the closest to “truth” for spatial variability in SWE across large areas (10s of km) and can directly provide estimates of snow-water volume throughout a watershed, if all of the watershed is flown and scanned.

ASO has been primarily deployed in several basins in California, most intensively the Tuolumne River Basin, and in the past few years ASO flights have covered the bulk of the southern Sierra Nevada range. In the Colorado River Basin, ASO has been flown as part of pilot projects in the Uncompahgre Basin (2013–2017), Gunnison Basin (2016, 2018–19), over

What is LiDar?

LiDAR, *Light Detection and Ranging*, is a remote sensing method that uses light in the form of a pulsed laser to measure variable distances to the Earth. These light pulses—combined with other data recorded by the airborne system—generate precise, 3-D information about the Earth’s surface characteristics.

From NOAA:
<https://oceanservice.noaa.gov/facts/lidar.html>

Grand Mesa (2013–2017), and in the Blue River Basin (2019; for Denver Water). Typically, 1–6 flights are carried out per basin per season.

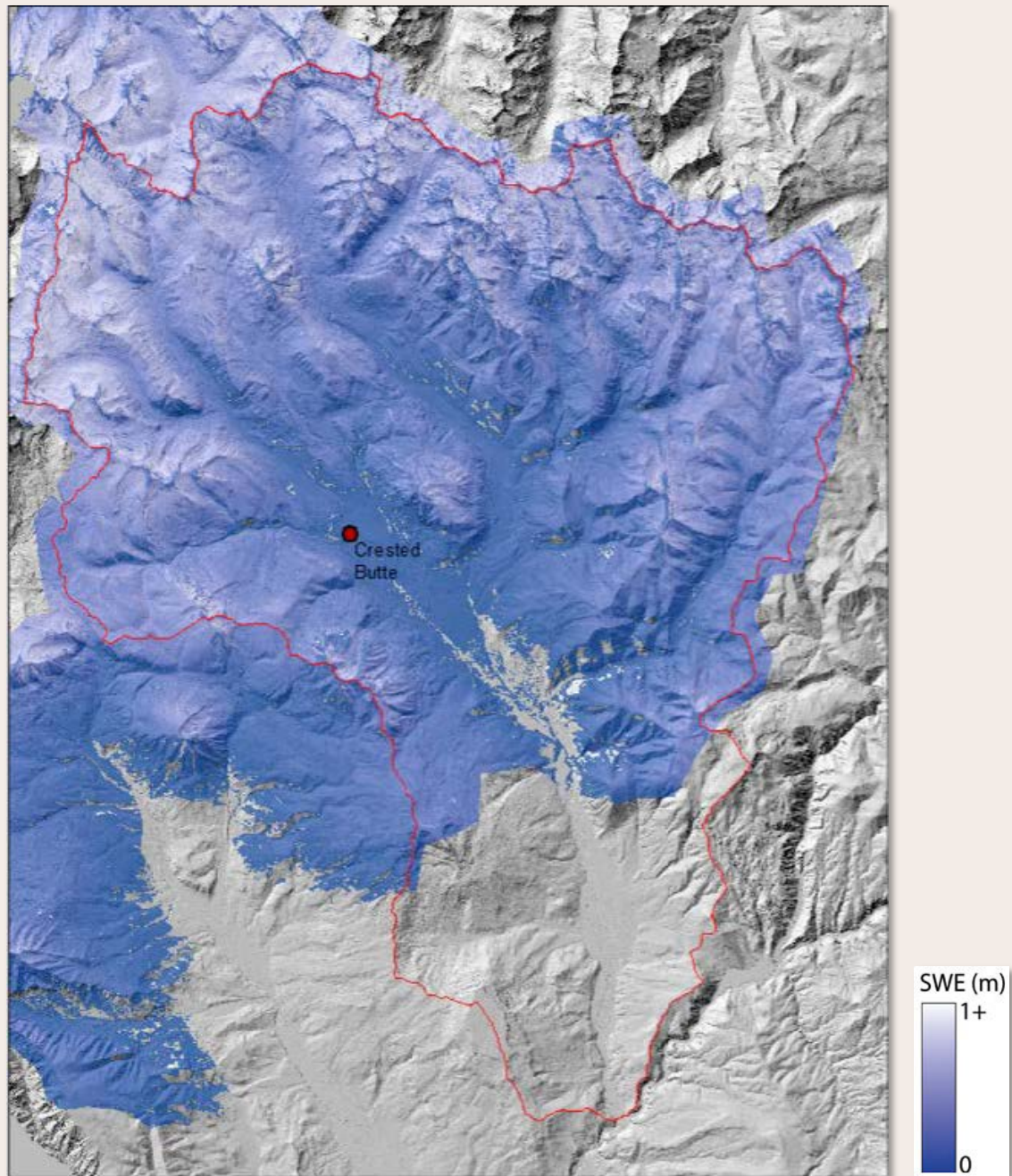


Figure 5.4

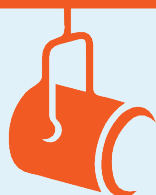
ASO-estimated SWE conditions based on airborne LiDAR snow-depth observations for the East River Basin around Crested Butte, April 1, 2018. The very fine spatial detail within the snow-covered area (blue shades) results from snow depth and SWE being driven by terrain features at multiple scales. (Source: Jeff Deems, CU CIRES and NASA/JPL)

California water agencies that have used ASO SWE data to produce or adjust water supply forecasts have found reductions in forecast error versus forecasts based only on in situ SWE data, allowing better optimization of reservoirs (Friant Water Authority 2019). This is particularly true during the latter portion of the melt season, when the remaining snow is at high elevations where it is poorly captured by the in situ network. At those times, the ASO-estimated SWE volume can effectively provide a lower bound on runoff that has yet to come. Previously collected ASO data are not publicly accessible, but generally can be obtained from ASO investigators.

The CBRFC and NASA JPL are working collaboratively to evaluate the ability to incorporate remotely sensed snowpack information from ASO into CBRFC models to improve water supply and streamflow forecasts. Although limited in frequency of data collections and spatial domain, ASO data is available over the Senator Beck region in the Uncompahgre River Basin, the East River, Ohio Creek, and Taylor Park regions in the Gunnison River Basin, and the Blue River. The CBRFC indicates they will continue to stay informed regarding the availability of ASO and other remotely sensed snowpack information, and its potential for incorporation into operational forecasting.

Because users typically pay for data capture and processing on a per-basin/per flight-basis, ASO appears to have higher costs compared with SNOTEL, satellite data, and the other spatially distributed snow products described below. However, the costs associated with these other platforms and methods, while often not as apparent to individual users, are still real and need to be considered within a broader context of regional priorities. Streamflow forecast errors associated with inadequate characterization of snowpack also incur real costs. For ASO and any other snow monitoring data, the value of the information and return on investment may be more relevant metrics than simply the cost of the product per unit area.

SPOTLIGHT



Winter orographic cloud seeding to enhance snowpack

Winter orographic cloud seeding involves introducing very small particles, typically silver iodide, into clouds that contain supercooled ($<0^{\circ}\text{C}$) water droplets. The particles serve as nuclei for ice crystals that grow as the water droplets freeze onto them, until they are too heavy to remain aloft and fall out as snow. The small silver iodide particles are most often released into clouds from ground-based generators; aircraft-based seeding appears to be more effective but is much more expensive (Flossmann et al. 2019). Orographic cloud seeding is done on the windward side of mountain ranges in order to leverage the natural enhancements by precipitation and snowfall by mountain barriers. The concept of orographic cloud seeding is inherently attractive, as even a small enhancement in precipitation and snowpack will, in principle, produce additional runoff at a lower cost than other sources of new water (Rauber et al. 2019).

In the 1960s and 1970s, several cloud-seeding programs were carried out in different parts of the Upper Basin on an experimental or operational-research basis. The largest of these, Reclamation's Colorado River Basin Pilot Project (CRBPP), was focused on the San Juan Mountains and lasted from 1970 to 1974. Reclamation was prepared to use the findings of that pilot project to design and conduct a region-wide operational cloud-seeding program (Weisbecker 1974), but the final report was inconclusive regarding the effectiveness of the CRBPP, and called for further research and pilot efforts instead of an operational program.

Over the next 40 years, there was a marked shift in the impetus and funding for cloud seeding research and operations in the western U.S., from federal agencies to state, local, and private entities (National Research Council 2003). During this period, two narratives about the efficacy of cloud seeding have emerged. The scientific community asserted, multiple times, that controlled experiments and other studies had been unable to demonstrate winter precipitation enhancements that were unambiguously attributable to cloud seeding in the Upper Basin or elsewhere (National Research Council 2003; Reynolds 2015). On the other hand, private firms carrying out operational winter cloud seeding programs, and their clients, have consistently claimed to see evidence of precipitation enhancement in seeded basins, typically a 5–15% increase on a seasonal basis.

Across the Upper Basin, the state water agencies and many water districts and ski areas have clearly endorsed the cost-effectiveness of cloud seeding by sponsoring and conducting numerous cloud-seeding programs, the longest-running of which began in the mid-1970s. As of 2019, there were seven cloud-seeding programs operating in western Colorado, three programs in central and southern Utah; and two in Wyoming, including a long-term, ground-based program in the Wind River Range, and a newer, aerial-based program in the Medicine Bow and Sierra Madre Ranges. Since 2007, the Lower Basin states have funded some of these programs; in 2018, entities representing all seven basin states signed a new agreement to continue funding coordinated cloud-seeding programs in the Upper Basin through 2026.

It remains difficult to isolate and quantify the effect of cloud seeding on snowfall totals and SWE (i.e., signal), given the complicated physics, the range of factors that can affect precipitation formation, and the large spatial and temporal variability in snowfall (i.e., noise). Researchers have used both modeling and field programs to investigate the effectiveness of cloud seeding projects. Modeling studies rely on advances in the modeling of cloud microphysics and seeding processes. Field programs need to extend for a long period of time (multiple seasons) and cover a large spatial area to support statistically meaningful findings (Flossmann et al. 2019).

Active from 2008–2013, the Wyoming Weather Modification Pilot Project (WWMPP) was explicitly designed to evaluate the effectiveness of cloud seeding in Wyoming’s Sierra Madre and Medicine Bow ranges (NCAR 2014; Rasmussen et al. 2018). In a companion study, researchers using aircraft-based radar found increases in boundary layer reflectivity, which implies an increase in the snowfall rate, following ground-based seeding activities as part of the WWMPP (Geerts et al. 2010; 2013). Preliminary analyses of the WWMPP results indicated an increase in snowfall with cloud seeding of 5–15% in “seedable” storms, although seedable conditions occurred in only about 30% of the season’s storms (NCAR et al. 2014). Thus, the corresponding increase in seasonal snowfall would be more on the order of 1.5–4.5%. The researchers later conducted a more systematic assessment of the WWMPP results using both statistical methods and high-resolution atmospheric modeling. The statistical analysis was unable to identify a statistically significant effect of ground-based cloud seeding, while the modeling study estimated that seeding enhanced annual precipitation by about 1.5% (Rasmussen et al. 2018).

In 2018, researchers were finally able to observe the long-theorized microphysical process for seeding-induced snow formation in action, during an operational cloud-seeding project in Idaho (French et al. 2018; Tessendorf et al. 2019). This was a major breakthrough in the scientific understanding of cloud seeding, with the potential to lead to improved monitoring of cloud seeding programs and better quantification of its impacts (French et al. 2018). At this point, one can say that cloud-seeding “works,” in that it clearly enhances snowfall along the path of the seeded particles; there are still large uncertainties in how that enhancement scales up to a seasonal basin-wide effect in the context of a specific operational program.

The prevalence of cloud-seeding programs in the Upper Basin also raises some issues for snowpack monitoring and its application. Measurements of SWE in locations with active cloud seeding programs may reflect greater values than natural processes alone would have produced (Julander and Bricco 2006). Such influences could potentially affect both snowpack trend analyses and the calibration of streamflow forecast models. Similarly, seeding-enhanced runoff could influence the analyses of streamflow trends and climate-streamflow relationships.

Spatially distributed modeled snow products

Spatially distributed snow modeling uses spatially variable meteorological conditions and modeled physical processes to produce snow state and snow flux estimates specific to each location or grid cell across a basin. For water supply purposes, the key output of such modeling is estimate of SWE for each pixel or other modeling unit across a basin, such that the total volume of basin-wide SWE can be tabulated directly from the smaller units. Thus they compensate for the key limitations (spatial density, representativeness, and elevational coverage) of the SNOTEL network. Equally critically, spatially distributed modeling also generates insights into processes, sensitivities, and patterns in time and space that are difficult or impossible to glean from point observations alone.

It is important to note, though, that spatially distributed modeled snow products are not independent of SNOTEL. All of the products described below either calibrate/validate their respective models on SNOTEL data, or directly assimilate SNOTEL data, or both, to inform the SWE estimates. They use spatial SWE estimates from a process model, and (in most cases) remotely sensed snow data, to in effect “spread” the SNOTEL observations across the landscape, generating a snowpack that is consistent with the SNOTEL observations but fills in the spatial gaps and detail. Accordingly, the SWE estimates from any of these products will be more uncertain in the elevation bands below and above the bulk of the SNOTEL network.

It is also difficult to independently validate (i.e., apart from SNOTEL) the accuracy of these spatial SWE products. Comparing them to each other can identify systematic differences, but not which product is “right.” ASO SWE data, however, can serve as a viable reference for those basins and dates for which ASO flights have been carried out (Oaida et al. 2019).

CBRFC modeled snowpack

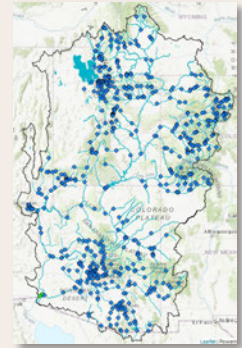
For operational streamflow forecasting, the CBRFC pairs a snow model (SNOW-17) with a hydrology model (Sac-SMA; see Chapter 8). SNOW-17 is run in a spatially “lumped” or partially distributed framework, meaning that area averages are calculated for each modeling unit, with each unit typically representing an elevation zone, of which there are usually three in each watershed. The mean area precipitation for a modeling unit is calculated from the precipitation observations at one or more SNOTEL or COOP stations, using weightings determined by model calibration and the PRISM precipitation climatology (Bender et al. 2014). In the Upper Basin, 6-hourly precipitation data is used, while in the Lower Basin, hourly data is used. SNOW-17 then builds a simulated snowpack, using the temperatures observed at the SNOTEL sites and local freezing levels, to determine whether precipitation is falling as snow or rain, and whether the snowpack is accumulating or ablating. Historical precipitation observations are used

to calibrate the snow model. The model effectively estimates a snow-water volume for each modeling unit, and thus for each watershed, sub-basin, and basin, which is then used to model the forecasted spring-summer streamflow volume (Bender et al. 2014). The model allows snow to persist at the highest elevations even after most or all SNOTEL sites have melted out, consistent with real-world behavior of the snowpack.

The operational estimates of snow-water volumes for each modeling unit are now available on the CBRFC website, accessible from the water supply forecast evolution plot for a given forecast point (Figure 5.5).

The CBRFC also computes a % median SWE for each modeling unit, and generates maps with these values (Figure 5.6) that can be accessed under the Snow Conditions menu item on the CBRFC [home page](#). The CBRFC is increasingly using additional snow information to supplement the modeled SWE from Snow-17 in their forecasting procedures; see below for more details.

**CBRFC Colorado Basin
River Forecast Center**



Link:
<https://www.cbrfc.noaa.gov/>

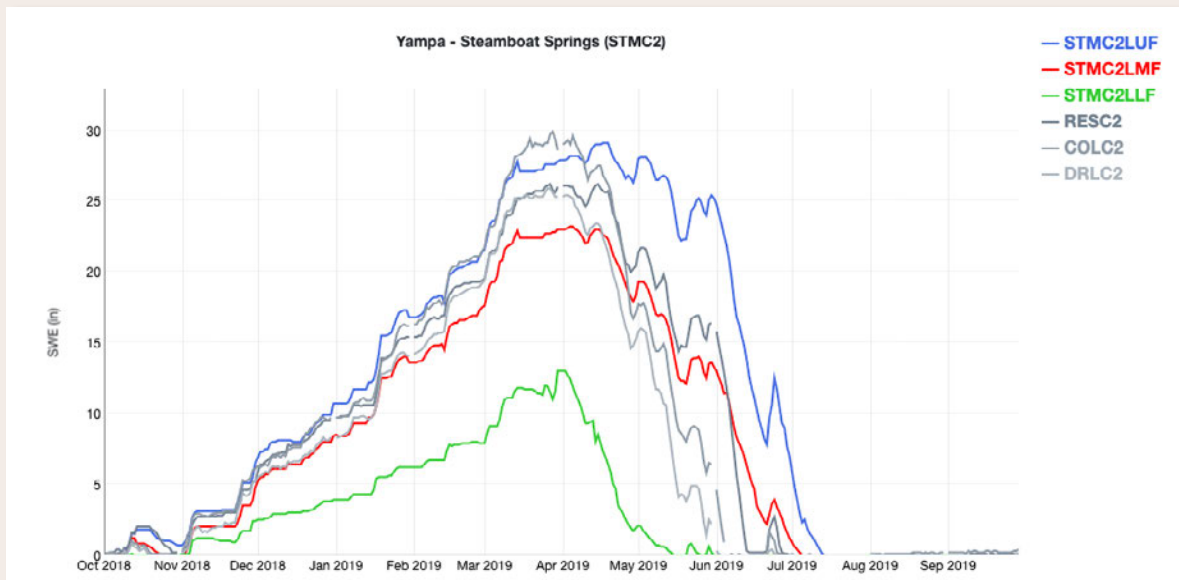


Figure 5.5

CBRFC modeled area averaged SWE during Water Year 2019 for the three modeling units (“Basin Zones”) comprising the catchment above the Yampa at Steamboat Springs forecast point: upper-elevation unit (>10,000’; blue line), mid-elevation unit (8500-10,000’; red line), and low-elevation unit (<8500’; green line). The three gray lines are observations from the three SNOTEL sites within the catchment, at elevations from 8400’ to 9400’. (Source: NOAA CBRFC; https://www.cbrfc.noaa.gov/dbdata/station/snowmodel/snowmodel_dg.html?id=STMC2)

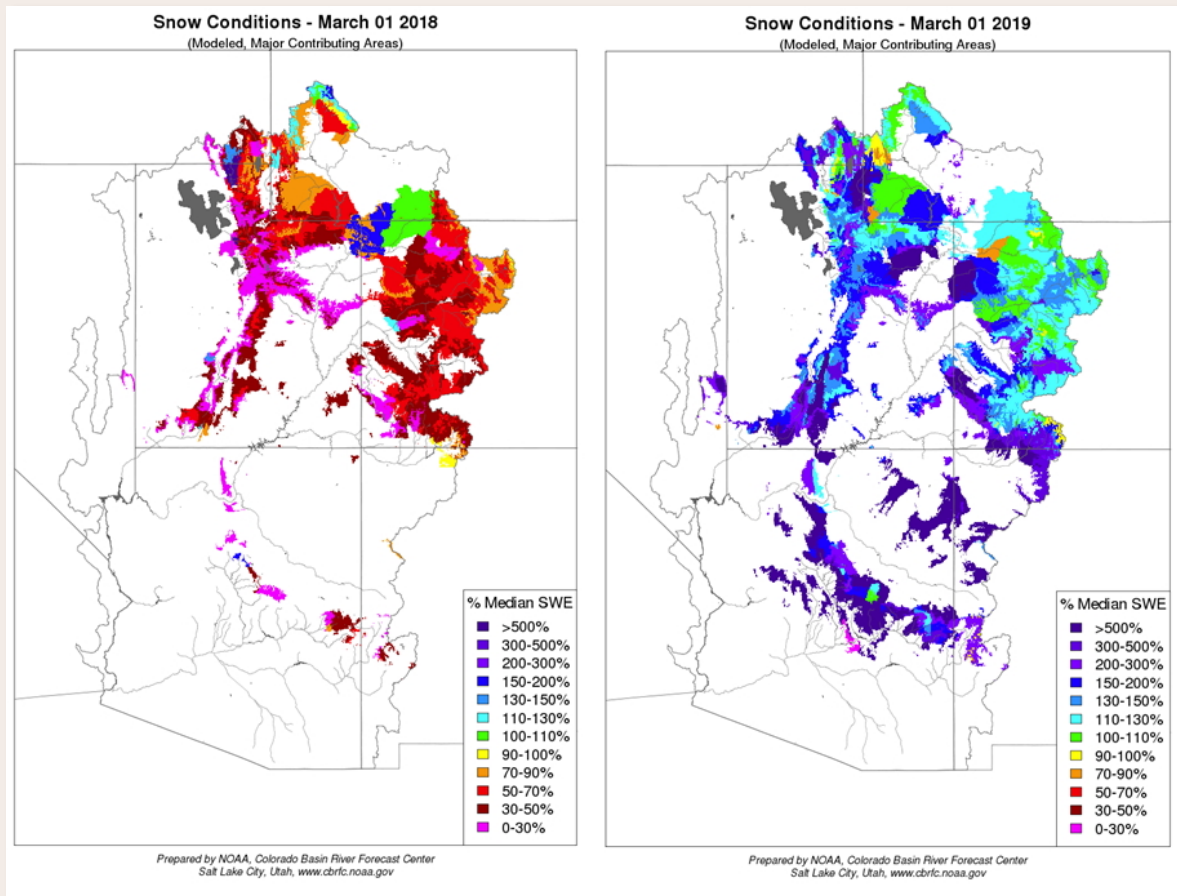


Figure 5.6

CBRFC modeled snow conditions (% of median SWE) for March 1, 2018 (left) and March 1, 2019 (right) showing both the broad contrast between an unusually dry and unusually wet winter, and the finer scale spatial differences. The CBRFC snow model is “lumped” or “partially distributed,” meaning that conditions are estimated for each model unit (multiple elevation bands in each watershed) but not on a gridded, pixel-by-pixel basis. (Source: NOAA CBRFC; <https://www.cbrfc.noaa.gov/rmap/grid800/index.php?type=snow>)

SNODAS (NOAA NOHRSC)

The Snow Data Assimilation System (SNODAS) was developed by NOAA’s National Operational Hydrologic Remote Sensing Center (NOHRSC) and been produced operationally for the U.S. since 2004. SNODAS estimates multiple snow characteristics on a daily basis by merging satellite, airborne, and in situ snow data with modeled depictions of snow cover (Barrett 2003). The snow variables that are modeled and made available include SWE, snow depth, snowmelt, sublimation, and snowpack average temperature. Model calibration and validation are focused primarily on SWE because of its importance to water management.

SNODAS is a physically based energy- and mass-balance snow model, driven by near real-time weather variables that can assimilate available snow data from remote sensing and in situ measurements. NOHRSC analysts decide on a daily basis whether to adjust model output in order to correct for discrepancies between measurements and model estimates (Hedrick et al. 2015). The final snow products have a spatial resolution of about 1 km over the conterminous United States (Figure 5.7).

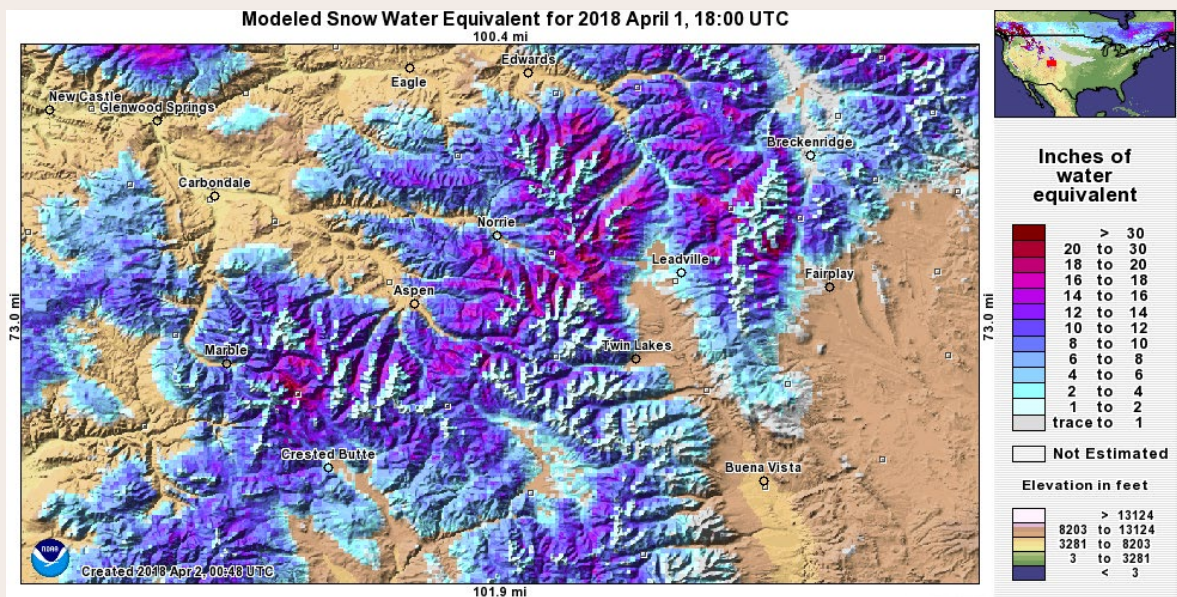


Figure 5.7

SNODAS modeled SWE for April 1, 2018 for a portion of the Colorado River headwaters and Gunnison Basin in western Colorado, showing the 1-km resolution of the SWE product. The SNODAS interactive map allows viewing of spatial data at multiple scales, and also time series for user-selected basins. (Source: NOAA NHRSC <https://www.nohrsc.noaa.gov/interactive/html/map.html>)

Three studies have assessed the accuracy of SWE or snow-depth estimates from SNODAS through comparison with high-density, in situ snow sampling in Colorado (Clow et al. 2012; Hedrick et al. 2015) and Idaho (Anderson 2011). These studies indicated that SNODAS snowpack estimates were reasonably accurate and useful at watershed scales (>10 km), more so than at the ~1 km (single pixel) to ~10 km scale, where there could be systematic errors in areas with substantial wind scouring and redistribution, such as above treeline, or on forested slopes with complex topography. While there have been a number of improvements to the SNODAS model and data assimilation scheme over time, including some that may have addressed the shortcomings identified in those studies, these changes are not well documented.

In 2016, the Colorado Water Conservation Board (CWCB) funded the development of a prototype map-based web tool by the Open Water Foundation to access and display SNODAS SWE data, including average SWE and total snow-water volume, for hundreds of basins covering Colorado. This tool is now operational on the [CWCB website](#) (Figure 5.8). The development of this tool by CWCB speaks to the interest in and demand for spatial snow data.

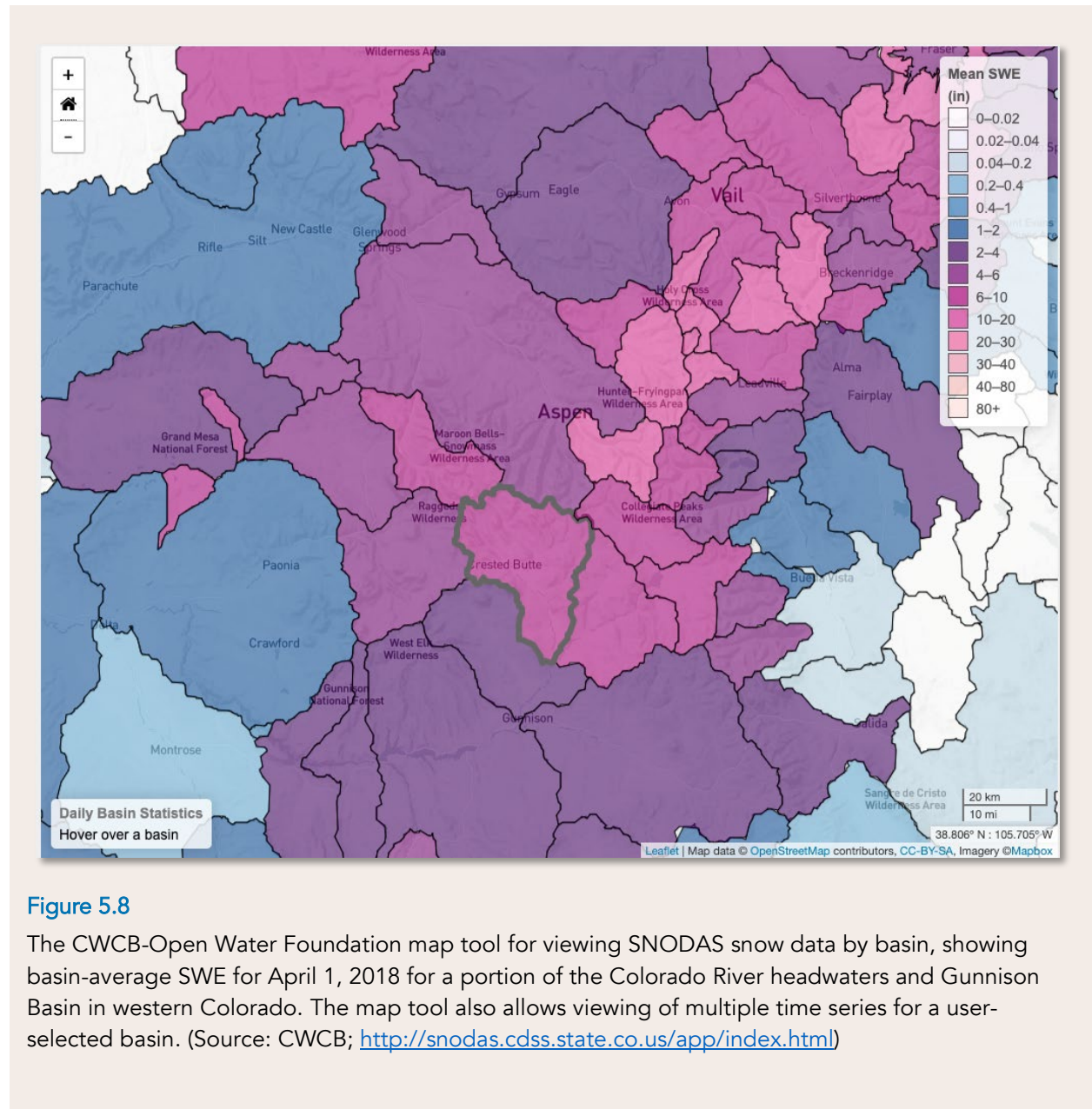
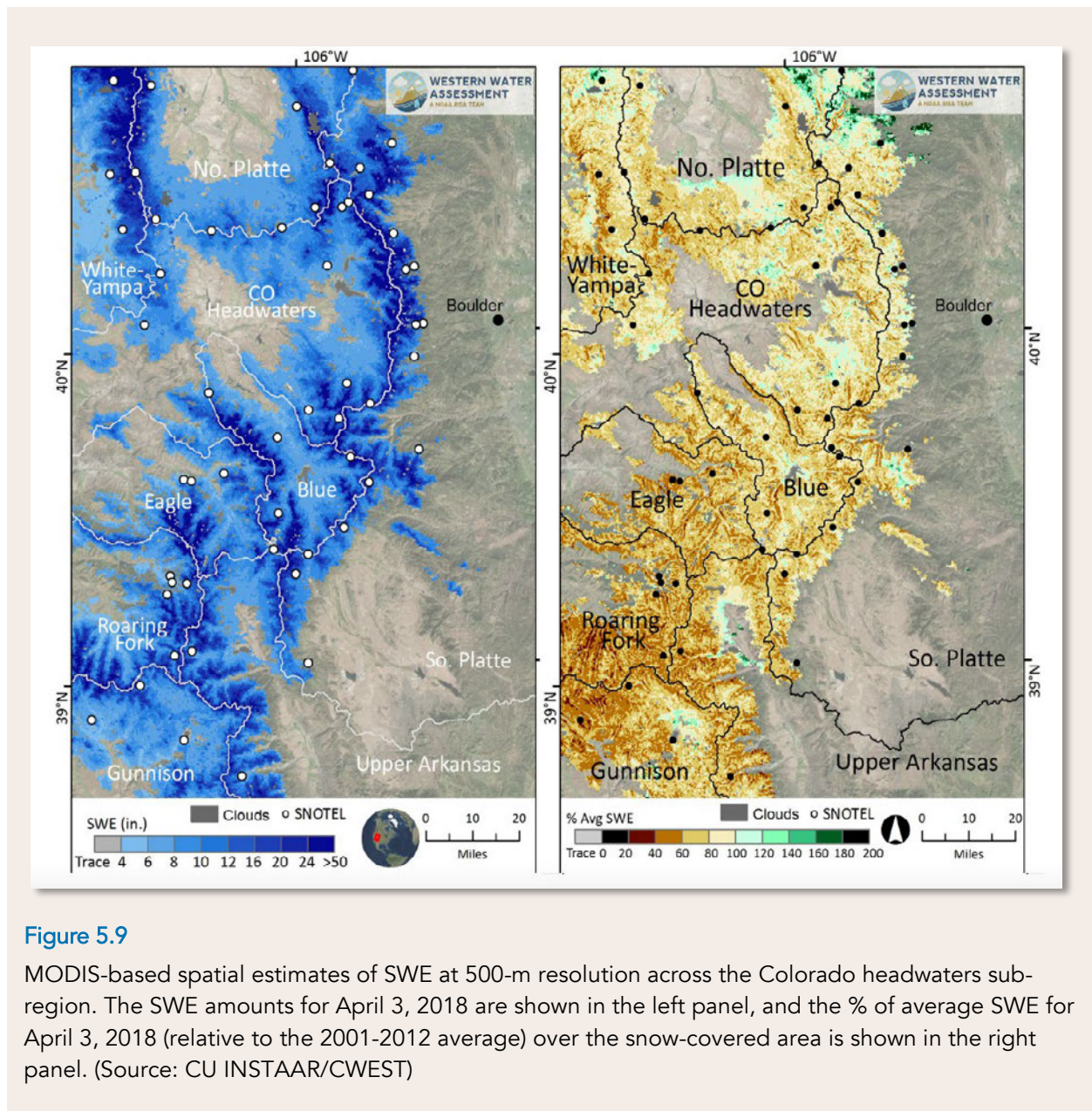


Figure 5.8

The CWCB-Open Water Foundation map tool for viewing SNODAS snow data by basin, showing basin-average SWE for April 1, 2018 for a portion of the Colorado River headwaters and Gunnison Basin in western Colorado. The map tool also allows viewing of multiple time series for a user-selected basin. (Source: CWCB; <http://snodas.cdss.state.co.us/app/index.html>)

MODIS-based spatial estimates of SWE

Researchers at the University of Colorado (INSTAAR and CWEST) have developed a method to obtain MODIS-based 500-m resolution spatial estimates of SWE. This is an experimental research product using a method that was originally developed for the Sierra Nevada (Guan et al. 2013). A near real-time product has been generated biweekly during a February-June season for water managers in California since 2012. The methodology was later refined and extended to two additional domains: Southern Rockies, which includes all of the Upper Basin and the northern portion of the Lower Basin (Schneider and Molotch 2016), and Northern Rockies, which includes northern Wyoming, Montana, and eastern Idaho.



For the Southern Rockies domain, a linear regression model is used to effectively blend the data listed below.

- Observed SWE at the approximately 300 SNOTEL sites and at 2,100 CoCoRaHS observer sites in the domain, scaled by the fractional snow-covered area from MODSCAG data from that day.
- Physiographic variables that affect snow accumulation, melt, and redistribution, including elevation, latitude, upwind mountain barriers, and slope.
- An analogous historical daily SWE pattern (2000–2012) that was retrospectively generated using historical MODSCAG data, and an energy-balance snow model that reconstructs peak SWE given the fractional Snow Covered Area (SCA) time series and meltout date for each pixel.

The linear regression model generates estimated SWE values for each pixel, out to the edges of the snow covered area shown in the MODSCAG image. The method works best in the spring, near or after the peak SWE (February–May). The SWE data are distributed in a multi-page report that includes maps (e.g., Figure 5.9), a summary of current conditions, and summary statistics.

In spring 2018 and 2019, this product was produced and distributed 4-5 times per season with the support of Western Water Assessment, and it is being produced again in spring 2020.

SWANN: The Snow Water Artificial Neural Network

The SWANN modeling system is a research product, developed at the University of Arizona, that uses snow models, assimilated in situ SWE data, and artificial neural networks (ANNs), a type of machine learning algorithm, to generate gridded estimates of SWE and snow cover (Broxton et al. 2017). SWANN was prototyped for the Salt River Basin in Arizona, in collaboration with the Salt River Project (SRP). The SWANN SWE estimates, which are available back to the early 1980s, use ANNs to account for local variations in topography, forest cover, and solar radiation, while the snow cover estimates (generated on a limited basis), use ANNs that are applied to Landsat and MODIS satellite reflectance data. The models are trained with in situ SWE observations and aerial LiDAR SWE estimates from across the southwestern U.S. The SWANN SWE data are produced in near real-time, and delivered to SRP via a prototype decision support tool that provides daily-to-annual operational monitoring of spatial and temporal changes in SWE and snow cover conditions. The product also includes 35+ years of daily SWE estimates, allowing it to be used in modelling applications that require long-term SWE records.

The developers of SWANN have also created a beta map-based web tool ([SnowView](#)) to visualize and access SWANN SWE estimates for basins across the U.S., including the Colorado River Basin and individual sub-basins (Figure 5.10). The SnowView tool can also display SNODAS SWE for comparison, as well as SNOTEL SWE and USGS streamflow data. While there has not yet been a published evaluation of the near real-time SWANN SWE estimates, an earlier version of the dataset was evaluated against ASO SWE estimates in California, and compared with a variety of remotely sensed SWE and snow cover products (Dawson, Broxton, and Zeng 2018).

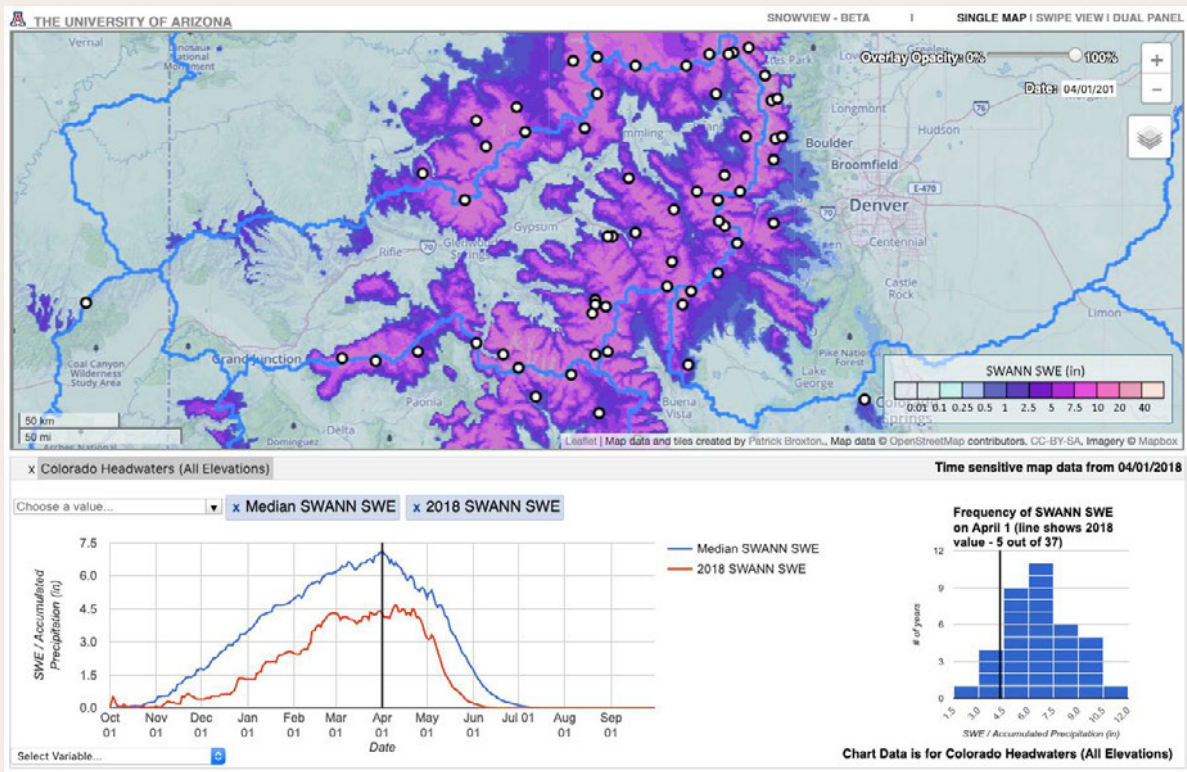


Figure 5.10

The SnowView map tool showing SWANN SWE estimates for the Colorado River headwaters and portions of adjacent basins for April 1, 2018. The seasonal curves in the lower left show the 2018 SWANN SWE for the river headwaters compared to the median for 2008-2019. (Source: SnowView, U. of Arizona; <https://climate.arizona.edu/snowview/>)

Challenges and opportunities in snow observations

As noted above, the SNOTEL snow-monitoring system serves its central purpose well, as indicated by the generally high skill of seasonal water supply forecasts that rely on SNOTEL data. However, the assumption of spatial representativeness underpinning these monitoring and forecasting systems is less robust in years with unusual conditions, e.g., an overall average snowpack with above average low-elevation snow. The larger

forecast errors that occur in these cases can potentially be reduced by better real-time characterization of those aspects of the snowpack's spatial distribution that are not captured well by SNOTEL. In order to take full advantage of this enhanced spatial information, though, streamflow forecasting systems need to be able to efficiently take in these data—which is not the case for the current CBRFC or NRCS systems.

The current snow monitoring and streamflow forecasting systems have also been built upon another assumption, that of *stationarity*: that temperature, precipitation, and SWE conditions at SNOTEL sites will maintain their statistical and model-calibrated relationships with seasonal and daily streamflow. This assumption is increasingly strained by non-stationarity in the hydroclimate system: warming temperatures and changing spatial and temporal patterns of snow accumulation and ablation. The current observation network and operational modeling capacities are not finely resolved enough—in space, time, or physical processes—to capture these changes, and therefore the usefulness of in situ measurements as robust indices of basin runoff production is at risk.

Ongoing efforts seek to add physical process representation to operational models in order to increase the capacity of runoff forecasting systems to handle diverse and changing watershed conditions, including climate change and variable dust-on-snow loading. This increased realism in turn demands data at higher spatial and temporal resolution. Over the past 15 years, new observing platforms, datasets, and modeling approaches have emerged, providing spatially distributed SWE information that builds on and complements the in situ point observations. New, remotely sensed data also capture additional snow characteristics, like albedo/dustiness, for which few in situ observations are available. As described above, some of these spatially distributed snowpack data are now used to inform operational streamflow forecasting by CBRFC, augmenting their partially distributed (“lumped”) modeled snowpack, for which precipitation observations from the SNOTEL network play a critical role.

An ideal future snowpack-monitoring system for the Colorado River Basin that is more robust to both year-to-year variability and long-term climate change will still require observations from the SNOTEL network at its core. But it would be increasingly augmented by remotely sensed/spatially distributed snowpack products, and feed into a streamflow forecast system that is itself upgraded to better handle spatial information and represent the physical processes of snow accumulation and melt that are undergoing change. Uncertainties related to the spatial and temporal representation of the snowpack would inevitably remain, but they would be much reduced. Ideally, CBRFC would continue to act as a testbed and integrator of these new snow data and methods, in partnership with university, agency, and private-sector researchers.



Dust-on-snow in the Colorado River Basin

Water managers, water users, recreationists, and residents alike have become increasingly accustomed to seeing pinkish to brownish color on the surface of spring snowpacks in the mountain headwaters of the Upper Basin, especially in western Colorado, from widespread deposition of desert dust. The dust's visual impact reflects physical changes that have already impacted the hydrology of the basin. Indeed, the emergence of accumulated dust at the top of the melting snowpack is increasingly recognized as the herald of the rapid end of the snow season.

Soil surfaces in the Colorado Plateau and Great Basin are naturally resistant to wind erosion thanks to physical and biogenic soil crusts, but these crusts are easily disturbed by land uses such as grazing, oil and gas drilling, dryland agriculture, and off-road vehicle use (Duniway et al. 2019). Once disturbed, the fine soil particles can be picked up by strong winds and transported hundreds of miles from the source. Dust-deposition events in the Upper Basin typically occur with large-scale storms that move in from the southwest, most frequently in the spring (Painter et al. 2007). The dust layers from each event are often buried by subsequent snows, but then reemerge and coalesce at the snow surface as the snowpack compacts and melts down in late spring.

Sediment cores from alpine lakes in the San Juan Mountains of Colorado show a seven-fold increase in dust deposition in the mid-1800s over the late Holocene average, coinciding with increased settlement and grazing (Neff et al. 2008). The deposition decreased somewhat after the late 1800s, but leveled off in the late 20th century at about five times the natural background levels, due to continued disturbance by an increasing array of agents. Dust deposition appears to have been on the increase again since the late 1990s, due to both increasing aridity in the dust source areas and increasing human disturbance of the soils (Brahney et al. 2013).

Field studies starting in the mid-2000s have demonstrated that dust loading in the snowpack increases the radiative energy absorbed by snow, enhances snowmelt rates, and leads to earlier timing of spring runoff (Painter et al. 2007; 2012; Skiles et al. 2012). Using the VIC (Variable Infiltration Capacity) hydrologic model (Chapter 6), two studies have quantified the likely impact of recent dust loading on both the timing and amount of runoff across the Upper Basin (Painter et al. 2010; Deems et al. 2013). Moderately dusty years like 2005 through 2008 are estimated to cause snowmelt and the peak of spring runoff to occur about three weeks earlier compared to the pre-1800s dust levels. The extreme dust loading—several times more than 2005–2008—that occurred in 2009, 2010, and 2013 is estimated to cause melt and runoff to occur another three weeks earlier, or a total of six weeks earlier than in the pre-historic hydrology.

The largest impacts are occurring in southwestern Colorado; the impacts generally decrease with distance from the Colorado Plateau (Painter, Bryant, and Skiles 2012; Skiles et al. 2015). From 2014 to 2018, there were no extreme dust years, but moderate to high dust years occurred in 2014 and 2016.

More recent work has demonstrated that the steepness of the hydrograph's rising limb on rivers in southwestern Colorado is tightly linked to the dust concentration—more dust means a steeper rise in flow—but is not correlated with spring air temperatures, indicating that dust is the far more important driver of melt (Painter et al. 2018). Changes to the slope and shape of the rising limb can impose constraints on water management, reducing the time window over which allocation decisions are made, or producing 'false peaks' which may trigger management decisions inadvertently.

Hydrologic modeling with the VIC model has also indicated that moderate dust loading has reduced natural streamflows at Lees Ferry by about 5% annually, or 800,000 acre-feet, compared to pre-1800s conditions (Painter et al. 2010). In the model, as the snowpack melts out earlier, more evapotranspiration occurs from soils and vegetation, reducing runoff. The additional dust loading in extreme dust years like 2013 only increases that loss from 5% to 6%, because meltout occurs so early that the sun angle is too low to drive much additional evapotranspiration.



View of the Senator Beck Study Plot at the Center for Snow and Avalanche Studies (CSAS), San Juan Mountains, Colorado, on May 5, 2013. The dark patches where that season's extreme dust accumulation has emerged at the surface sit lower than the adjacent cleaner snow, indicating the enhanced melt rate due to the dust. (Photo: CSAS Colorado Dust-on-Snow program.)

This dust-caused shift and reduction in runoff has likely been present in many water years since the early 1900s, so a moderate dust impact is partly embedded in what we consider normal. The spatial and year-to-year variability in dust loading, and resulting impacts on the hydrograph, complicate the streamflow forecast, and therefore basin operations. The accuracy of the Colorado Basin River Forecast Center (CBRFC) streamflow forecasts in the dust-impacted watersheds has been found to be linearly related to the amount of dust influence on snowmelt, with both unusually high and unusually low loading being associated with larger forecast errors, indicating that their model has effectively been calibrated to moderate dust levels over time (Bryant et al. 2013). The CBRFC now uses satellite data (MODDRFS) showing dust loading to adjust the temperatures in their model to force the model to melt snow faster, as described elsewhere in this chapter, though dust-on-snow effects may still contribute to forecast error.

Given the multiple snowmelt processes affected by dust, the modeled interaction of the projected future regional warming with the dust-on-snow effect is complex (Deems et al. 2013). Runoff timing is strongly affected by dust under all future warming scenarios, which means that dust reduction efforts could still have a beneficial impact on snowpack longevity even under a markedly warmer climate. However, there may be lower potential for recovery of annual runoff under high-warming scenarios. Because warming reduces snowpack amounts much more strongly than dust-induced evaporation losses, moving from moderate dust to extreme dust in a warmer future climate has no additional effect on runoff volume (Deems et al. 2013). A warmer future climate would also lead to drier soils in the dust source region, reducing vegetation cover and allowing for greater dust emission (Munson, Belnap, and Okin 2011).

It may be possible to at least partly reverse dust-on-snow impacts in the Upper Basin with management and policy changes (Duniway et al. 2019). Researchers continue work to determine how improved land-use practices or restoration efforts might reduce the amount of dust that is mobilized and ultimately deposited in the snowpacks of Colorado and the West, with funding from water management agencies in the Colorado River Basin. It is now understood that impacts to snowpacks from dust and other aerosols are a global phenomenon, increasing in many other regions due to anthropogenic disturbances similar to those in the western U.S. (Skiles et al. 2018).

The Colorado Dust-on-Snow (CODOS) dust monitoring program, conducted by the Center for Snow and Avalanche Studies, has been a critical source of information, providing dozens of updates throughout the snow season on their weather and dust observations, and integrated assessments of the seasonal impacts of dust on snowmelt and runoff. The CODOS program is funded by CWCB and the Basin Roundtables, Reclamation, Colorado River District, Denver Water, and several other water districts and utilities, indicating the relevance and utility of the CODOS data and assessments.

5.3 Streamflow observations and monitoring

Streamflow observations in the Colorado River Basin have formed the basis for the agreements, decrees, treaties, and compacts that comprise the Law of the River. They are critical to ongoing management and operations of all aspects of Colorado River Basin water supply today.

Observed (gaged) streamflow records are used directly in multiple ways, including real-time applications, streamflow forecasting, flood warning systems, reservoir operations, diversion scheduling, and ecological and recreational assessments. They are also commonly modified (e.g., to adjust for upstream activities), manipulated (e.g., to examine different sequences), or transformed (e.g., to fit a frequency distribution) for use in planning, research, and design. The gaged records are the starting point for all of these activities.

Gaged streamflows

The USGS is the primary entity that operates and maintains stream gages. Within the Colorado River Basin, Reclamation, the basin states, and dozens of other entities also maintain, operate and fund stream gages through their participation in the Cooperative Water Program (Interstate Council on Water Policy 2012). The USGS performs quality control and is the central clearing house for data collected through the Cooperative Water Program. Near real-time streamflow data as well as historical streamflow data are available for these stations through the [National Water Information System](https://waterdata.usgs.gov/nwis/) (NWIS).

Streamflow gage uncertainty

As is true with all data input to water resources models, “you cannot forecast any better than you can gage” (R. Julander, as quoted in Lukas et al. 2016). The USGS provides assessments of the gage quality of each streamflow gage, for each year. These annual accuracy assessments depend on the stability of the stage-discharge relationship (rating curve), which is used to convert the observed water elevation (stage) to streamflow (discharge). They also depend on the accuracy of the observations of stage, measurements of discharge, and interpretations of the records. The rated accuracy corresponds to 95% of the reported discharge data departing from the “true value” by the following percentages: excellent (<5%), good (<10%), fair (<15%), and poor (>15%) (US Geological Survey n.d.). USGS gage accuracy documentation can be found in the USGS Annual Water-Year Summaries for each gage, an example of which is provided in Figure 5.11.

USGS National Water Information System



Link:

<https://waterdata.usgs.gov/nwis/>

Water-Data Report 2012
09380000 COLORADO RIVER AT LEES FERRY, AZ

Upper Colorado-Dirty Devil Basin
Lower Lake Powell Subbasin

LOCATION.--Lat 36°51'53", long 111°35'15" referenced to North American Datum of 1927, in NE ¼ SE ¼ sec.13, T.40 N., R.7 E., Coconino County, AZ, Hydrologic Unit 14070006, in Navajo Indian Reservation, on left bank at head of Marble Gorge at Lees Ferry, just upstream from Paria River, 16 mi downstream from Glen Canyon Dam, 28 mi downstream from Utah-Arizona State line, and 61.5 mi upstream from Little Colorado River.

DRAINAGE AREA.--111,800 mi², approximately, including 3,959 mi² in Great Divide Basin in southern Wyoming, which is noncontributing (previously considered part of the Missouri River basin).

SURFACE-WATER RECORDS

PERIOD OF RECORD.--Jan. 1895 to current year. Estimates of monthly and annual discharge only for some periods, published in WSP 1313.

REVISED RECORDS.--WSP 859: 1921-23. WSP 1313: 1914-21.

GAGE.--Water-stage recorder. Datum of gage is 3,106.16 ft above sea level. Prior to Jan. 19, 1923, nonrecording gages or reference points within 400 ft of present gage, at different datums.

REMARKS.--Records good. Flow regulated since Mar. 13, 1963, by Lake Powell, 16 mi upstream. Many diversions above Lake Powell for irrigation, municipal, and industrial use. No diversions or inflow between Lake Powell and the gage.

AVERAGE DISCHARGE FOR PERIOD OF RECORD.--51 years (water years 1912-62), 17,850 ft³/s, 12,930,000 acre-ft/yr.

EXTREMES FOR PERIOD OF RECORD.--1895-1962: Maximum discharge, 220,000 ft³/s, June 18, 1921, gage height, 26.5 ft, from floodmarks, from rating curve extended above 120,000 ft³/s on basis of discharge computed for station near Grand Canyon; minimum, 750 ft³/s, Dec. 27, 1924.

1963-Curent year: Maximum discharge, 97,300 ft³/s, June 29, 1983, gage height, 18.14 ft; minimum daily, 700 ft³/s, Jan. 23, 24, 1963, result of closing coffer dam at Glen Canyon Dam.

EXTREMES OUTSIDE PERIOD OF RECORD.--Maximum discharge since at least 1868, about 300,000 ft³/s July 7, 1884, gage height, 31.5 ft, present site and datum, from floodmark at mouth of Paria River, from rating curve extended above 120,000 ft³/s on basis of discharge computed for flood of June 18, 1921, for station near Grand Canyon.

EXTREMES FOR CURRENT YEAR.--Maximum discharge, 21,200 ft³/s, Nov. 20, 21, 25, gage height, 10.83 ft; minimum daily discharge, 7,910 ft³/s, Sept. 9.

Figure 5.11

Typical USGS annual water-year summary for a streamflow gage. (Source: US Geological Survey 2018c)

Uncertainties in streamflow data arise from multiple possible sources and those sources are often noted in the gage documentation. They include equipment limitations, errors in the rating curve, errors in stage observations (due to ice, for example), errors due to the averaging methods used to obtain mean gage height, and changes in stream channel or vegetation (Hamilton and Moore 2012). Opportunities to measure extreme high or low flows are rare and brief, making such events difficult to capture and represent in the rating curves, and therefore subject to additional uncertainty. Finally, conversions to more automated stream gaging means fewer field visits to gages to observe and address site conditions (Hamilton and Moore 2012).

The combined uncertainties found in streamflow estimates have been summarized as follows: 50-100% for low flows, 10-20% for medium or high in-bank flows, and 40% for out-of-bank flows (McMillan, Krueger, and Freer 2012; McMillan et al. 2017). Cohn, Kiang, and Mason (2013) have offered a method that uses statistical techniques and on-site measurements to try to get better estimates of discharge uncertainty, and Kiang et al. (2018) have reviewed current methods of estimating discharge uncertainty and found that estimates vary widely from method to method.

Federal priority stream gages

A subset of USGS streamflow gages are part of the “[Federal Priority Streamgages](#)” (FPS) network, a group of gages that are considered critical for federal support of forecasting, compact and border agreements, analysis of long-term trends, and other purposes (US Geological Survey 2018a). The FPS network is considered the backbone of critical stream gages throughout the nation and was developed in order to give the USGS a systematic way to evaluate how and where funding and other support should be placed. The criteria used to determine which gages to consider priority gages are listed below.

1. Meeting Legal and Treaty Obligations on Interstate and International Waters (to monitor legal requirements for deliveries of water at state and national borders; presently 515 gage sites according to <http://water.usgs.gov/nsip/nsipmaps/federalgoals.html>)
2. Flow Forecasting (sites needed for validation and improvement of forecasts where the National Weather Service and other federal agencies carry out flood or water supply forecasts; 3,244 gage sites)
3. Measuring River Basin Outflows (for calculating regional water balances over the nation; 450 gage sites)
4. Monitoring Sentinel Watersheds (for determining long-term trends in streamflow across the country; 874 gage sites)
5. Measuring Flow for Water Quality Needs (for characterizing the quality of surface waters; 210 gage sites) (National Research Council 2004)

These active FPS gages are supported through a combination of federal and partner funding—less than one-quarter are fully funded by the USGS. The agency uses the FPS designation to indicate those gages that USGS classifies as critical and thus eligible for FPS funding as available from federal appropriations. For example, preventing the loss of long-term data collection stations, because of their value in assessing trends, recurrence frequencies of floods and droughts, and other variables, is of particular concern. The value of long-term streamgaging has been expressed by the National Research Council (2004):

USGS Federal Priority Stream Gage Network

Link:
<https://www.usgs.gov/mission-areas/water-resources/science/federal-priority-streamgages-fps>

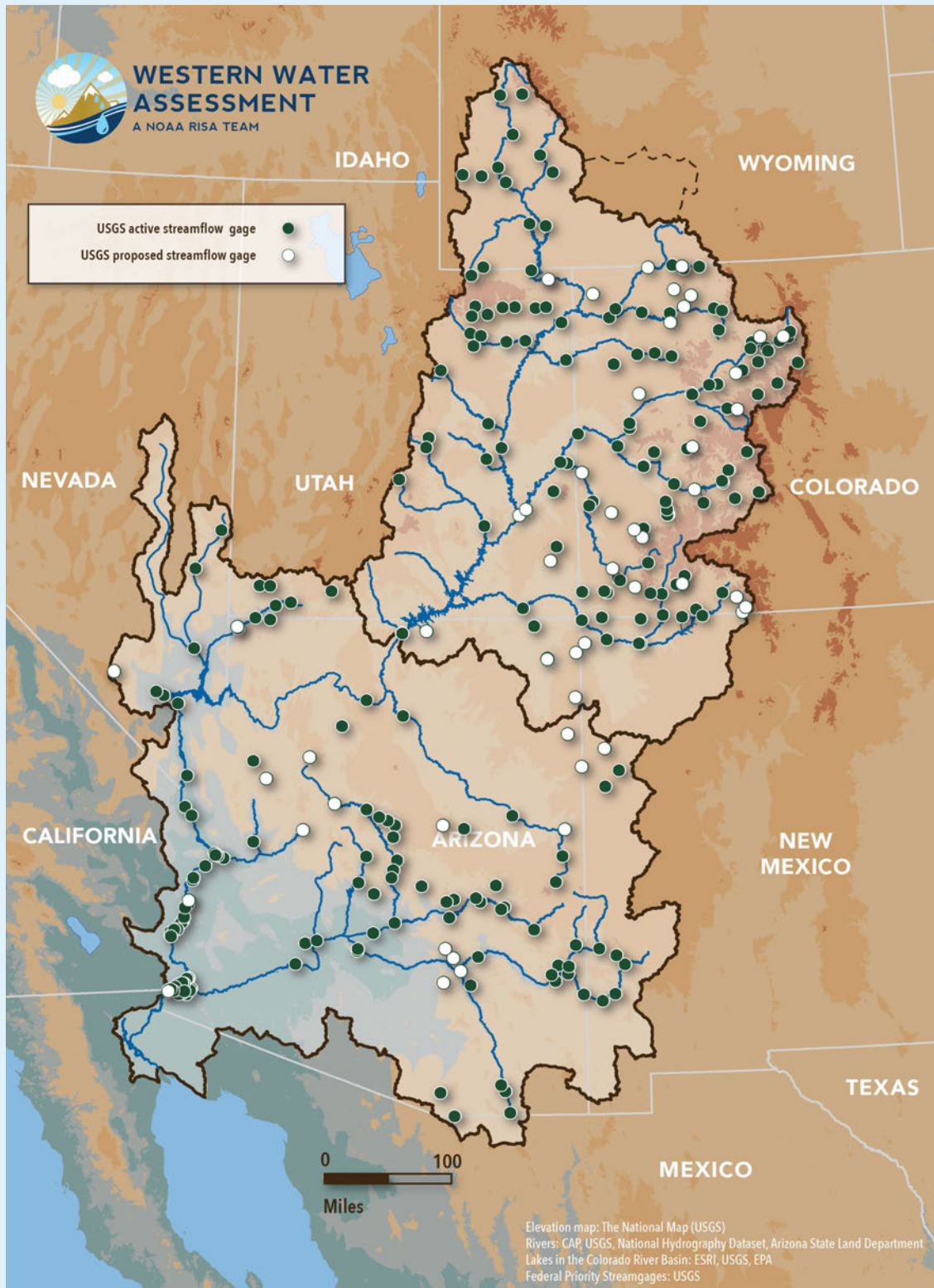


Figure 5.12

Map of active and proposed USGS federal priority stream gage locations. (Data: USGS; <http://water.usgs.gov/networks/fps/>)

“The streamgaging network ... has had to contend with unstable and discontinuous funding support. Gages have been inactivated when cooperators cut budgets, and these incremental losses have eroded the network. Many inactivated gages had long records that are valuable for trend analysis and forecasting. It is practically impossible to quantify the cost of losing an individual gage. Its value even for one goal—for example, flood or drought forecasting—is embedded in the operation and accuracy of the entire forecast system, the forecast delivery mechanisms, and the forecast response.”

National Research Council (2004)

Sixty percent of the FPS sites serve a forecast function. FPS streamflow gages in the Colorado River Basin for all purposes, both active and proposed, are shown in Figure 5.12. More detail about each station is available on the USGS’s FPS [website](#) by clicking on the individual gage and bringing up the station information. It is important to note that the FPS network streamflow gages shown on the map in Figure 5.12 are a subset of gages within the larger network of USGS streamflow gages that supply information for a diverse set of needs and therefore are not inclusive of all USGS streamflow gages.

Streamflow data gaps in the Colorado River Basin

In its 2016 report, “Looking Forward: Priorities for Managing Freshwater Resources in a Changing Climate,” the interagency Water Resources and Climate Change Workgroup (2016) recommended sustaining and expanding existing monitoring networks and data collection by identifying and addressing data gaps and needs for water resource management, and expanding adoption of regional monitoring networks to establish baseline conditions for evaluating impacts due to climate change. The first step in identifying streamflow data gaps is the national streamgage gap study by Kiang et al. (2013), which compiled information about each USGS gage and the basin areas contributing to it. For consistency, the authors focused exclusively on USGS gages and did not consider gages operated by other agencies or organizations. Within the Colorado River Basin, they list 619 total USGS gages: 405 in the Upper Basin and 214 in the Lower Basin. For comparison with gage coverage in other basins nationally, Figure 5.13 shows the location of smaller basins (<500 sq. mi.) for which streamflow is measured by at least one USGS gage. Of course, gage density will correspond, to some extent, to stream density, so arid regions will have lower gage density. In the Colorado River Basin, the smaller basins with gage coverage shown in Figure 5.13 are mainly located in higher-elevation areas that provide most of the basin’s runoff (Chapter 2).

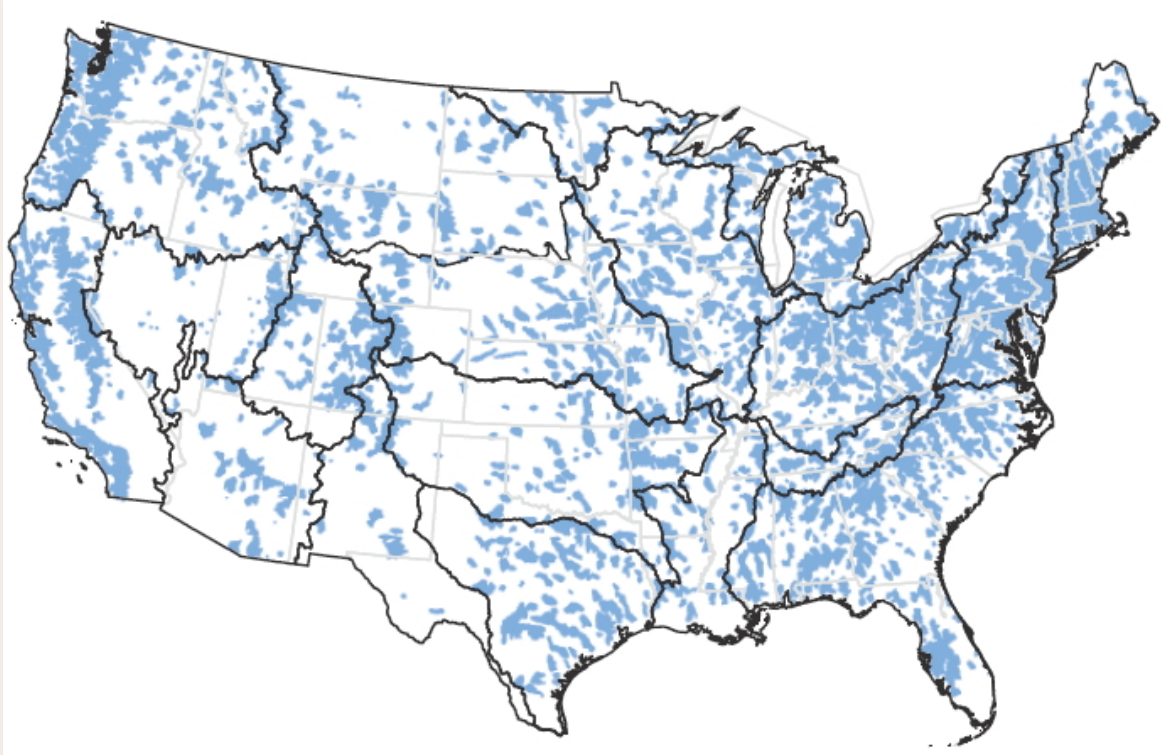


Figure 5.13

Basins of 500 square miles or less for which streamflow is measured. (Source: Kiang et al. 2013)

Kiang et al. (2013) also looked at the density of reference-quality gages, that is, those with relatively little human activity upstream that might impact the measured flow and are therefore of particular interest for researchers and planners looking for unimpaired data. They list 104 reference quality gages with 20 or more years of record in the Colorado River Basin, 68 in the Upper Basin and 36 in the Lower Basin, a fairly low density compared to other, more humid, parts of the country. As mentioned above, in the Colorado River Basin, stream gages are more common in the higher elevation watersheds. The USGS is beginning a new national gap analysis for stream gages in 2020 (M. Landers, pers. comm.).

Additional monitoring of Colorado River Basin streamflow has been suggested in the draft, joint Reclamation-CBRFC Forecast and Reservoir Operation Modeling Uncertainty Scoping (FROMUS) report to help reduce errors and uncertainty in 24MS forecasts and therefore in system condition projections. In particular, that report suggests that additional gaging at Upper Basin diversion sites and Lower Basin intervening flow locations could improve streamflow forecasts substantially (Reclamation and Colorado Basin River Forecast Center in preparation). The FROMUS report is discussed in more detail in Chapter 3.

Streamflow observations in the Colorado River Basin

Records of streamflow observations in the Colorado River Basin date back to the late 19th century. The longest record that is used in planning studies in the basin is the “Green River at Green River, UT” gage that has a period of record extending back to October 1894 (US Geological Survey 2018b). Perhaps the most important 19th century record is the “Colorado River at Lees Ferry, Arizona” gage, for which records begin in January, 1895 (US Geological Survey 2018c). The Lees Ferry gage measures flow in the Colorado River mainstem and is located just upstream of the mouth of the Paria River, and about a mile upstream of the Colorado River Compact point dividing the Upper Basin and the Lower Basin at Lee Ferry, Arizona.



Figure 5.14

Lees Ferry Gage in 1923. Photograph taken by G.C. Stevens of the U.S. Geological Survey just after sunset on September 22, 1923. (Source: Topping, Schmidt, and Vierra Jr. 2003)

A historical summary and analysis of the Lees Ferry gage describes the evolution of the gage from a staff gage that was read twice a day to a continuous recording strip chart gage to an instantaneous recording gage (Topping, Schmidt, and Vierra Jr. 2003). The Topping et al. report provides a wealth of information about measurement methods at Lees Ferry, hydrologic conditions prior to the closure of Glen Canyon Dam, characteristics of the channel at the gaging station, and analysis of the flood record prior to construction of the dam.

Within the Colorado River Basin, many individual gaging stations have documented idiosyncrasies, from station relocations (Colorado River near Glenwood Springs, CO), to missing seasons (Yampa River near Maybell, CO), to changes in equipment (Colorado River at Lees Ferry, AZ). For example, records from the Colorado River at Lees Ferry, AZ gage were rated “good” in 2006 through 2012, but were upgraded to “excellent” in 2013 through 2018.

The primary stream gaging stations used for planning and operations models in the Colorado River Basin are the 29 stations listed in Figure 5.15 and shown in the map in Figure 5.16. The numbers on the map are keyed to the station names in Figure 5.15, which shows the record lengths for the gage locations. The 29 stations have varying record lengths and therefore have varying levels of overlap with each other.

In 1983, Reclamation developed a “hydrology database” for its Colorado River modeling system; the record lengths shown in Figure 5.15 reflect the gage records in that database. The record lengths in Figure 5.15 don’t always correspond to the record lengths reported by the USGS for the gages—in some cases, the Reclamation record is longer. The gage locations shown on Figure 5.16 correspond to the inflow points for Reclamation’s CRSS model, described in Chapter 3, and therefore correspond to the locations where natural flows are calculated.

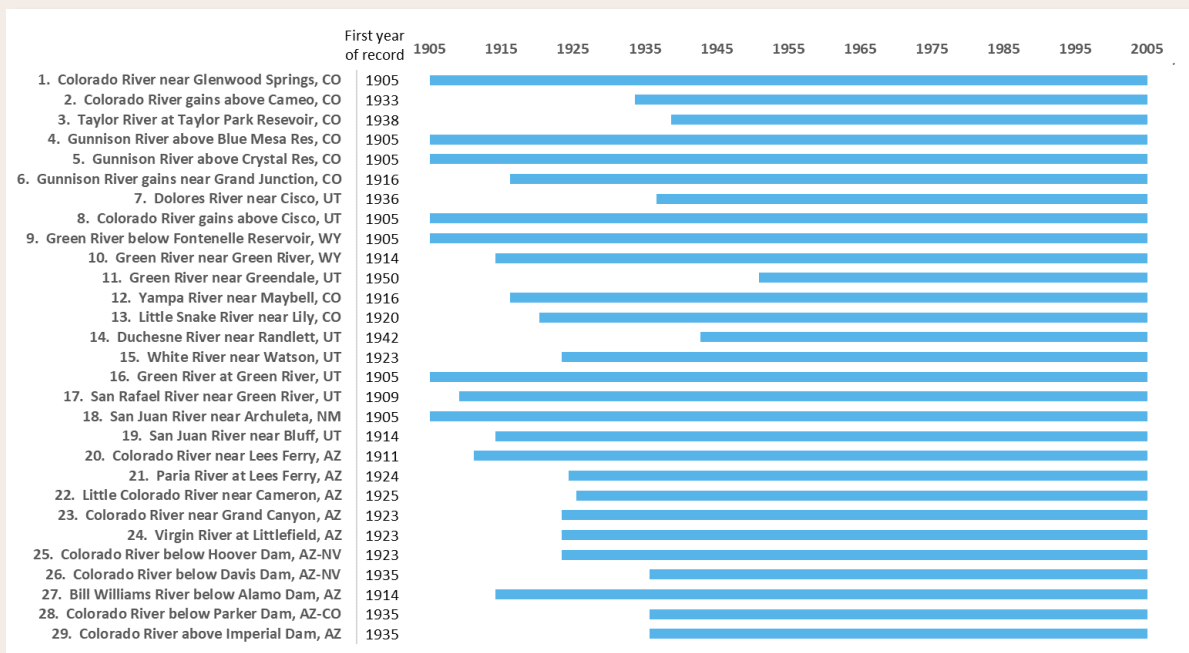


Figure 5.15

Gage names and record lengths for locations identified on the basin map in Figure 5.16, through 2005. (Source: adapted from Lee and Salas 2006)

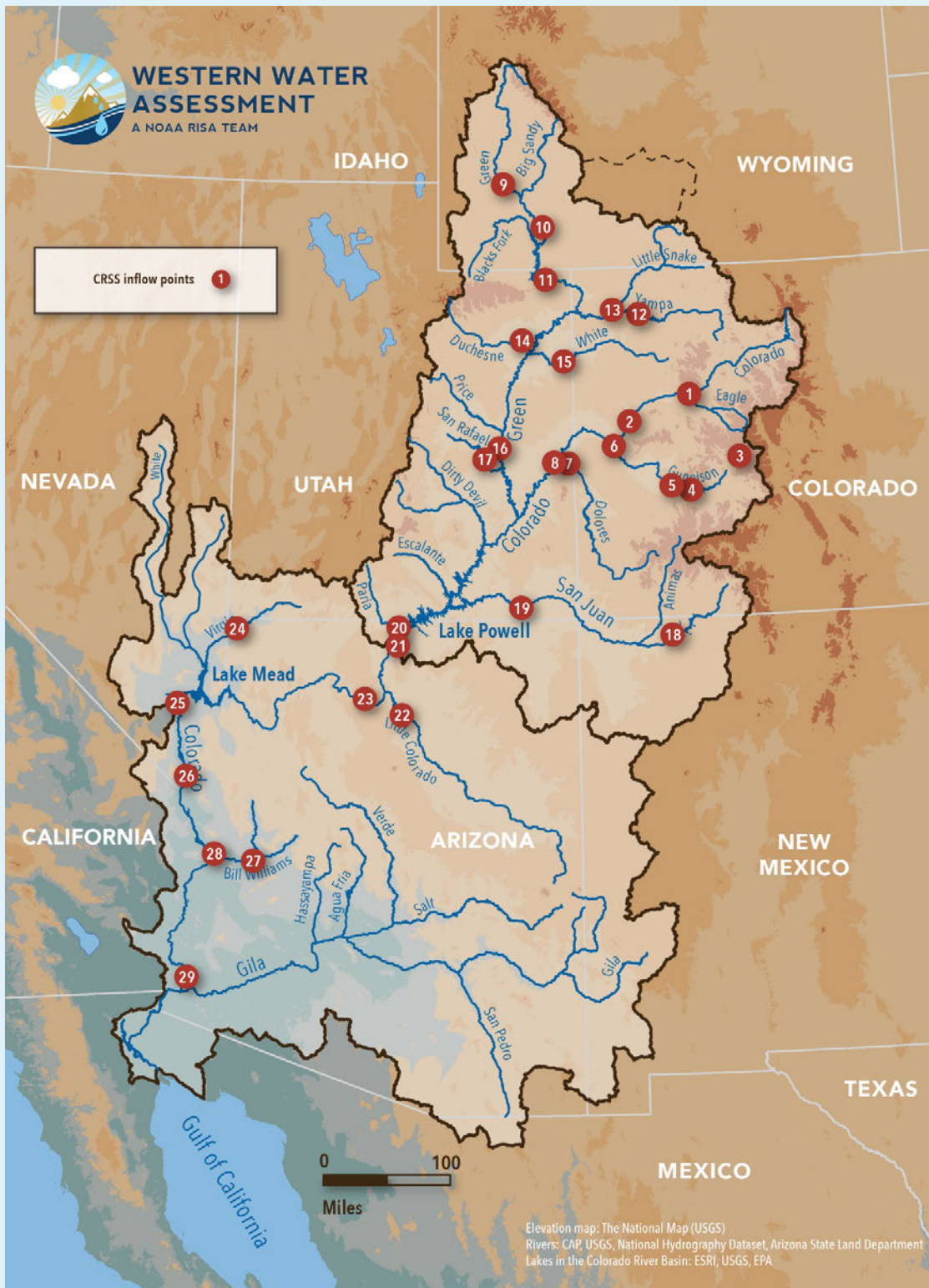


Figure 5.16

Primary gage stations used for Reclamation’s planning and operations models. The names and record lengths for the numbered locations are provided in Figure 5.15

Naturalized and unregulated flows

Streamflow data obtained directly from gages reflects contemporaneous upstream natural processes and human activities such as diversions, agricultural return flows, and reservoir operations. The time series reflects changes in those natural processes and human activities over time as climate, vegetation, and land use in the basin change. These homogeneities in the observed streamflow record, if quantifiable, may be reduced through “naturalization” of the record. That is, if quantitative information about upstream activities is available or can be developed, it can be used to adjust gage observations to calculate streamflows that are restored to natural, unimpaired levels.

The USGS provides some documentation of upstream effects on observations at the gages. For example, the USGS 2019 annual water year summary for the “Gunnison River near Grand Junction, Colorado” gage describes its observations as affected by upstream activities thus: “Natural flow of river affected by diversions for irrigation of about 233,000 acres upstream from station, storage reservoirs, and return flow from irrigated lands.” However, the USGS documentation of upstream activities is both very coarse and only infrequently updated. For example, the 2019 description of upstream activities for the Gunnison River near Grand Junction gage is almost identical to one published for water year 1975 (U.S. Geological Survey 1977). Streamflow naturalization requires finer temporal and spatial estimates of upstream impacts.

The three Reclamation models described in Chapter 3 simulate the fate of runoff under existing or potential policies, and account for either current system development and demands or different projections of future development and demands. If the inflow datasets used by those models were simply gaged streamflows, the results would be confused by the inhomogeneities in the record. Therefore, prior to use in the Reclamation models, the gaged record needs to be adjusted, or naturalized, to approximate the flows that would have been observed in the absence of human activity. The level of adjustment depends on the model, the time step, and the availability of data quantifying upstream activities.

The process of naturalizing the streamflow gage data differs somewhat among the entities that develop and maintain naturalized streamflow datasets. The State of Colorado, the Upper Colorado River Commission (UCRC), Reclamation, and the CBRFC each produce versions of adjusted gage flows at selected locations in the basin. A summary of these products is provided in Table 5.2 and described briefly below the table.

Table 5.2

Adjusted flow records that are currently used in the Colorado River Basin.

Entity	Naturalized flow label	Locations	Time step and period	Application	Reference
State of Colorado	Baseflow	214 points in Colorado	Monthly 1950–2005	StateMod	Colorado Water Conservation Board (2012)
UCRC	Virgin flow	Lee Ferry (the Colorado River Compact point)	Annual, 1896–present	Reporting	UCRC (2017, 2018)
Reclamation	Natural flow	29 points throughout the Colorado River Basin	Monthly, 1906–present	CRSS, and most long-term basin research studies	Prairie and Callejo (2005)
CBRFC	Unregulated flow	159 sites throughout area of responsibility	Monthly and seasonal 1964–present	24MS and MTOM and stakeholders' forecast needs	See Table 3.1 in Chapter 3
Reclamation	Unregulated flow	9–12 points in the Upper Basin	Daily and monthly, 1964–present	Contributes indirectly to 24MS and MTOM	See Table 3.1 in Chapter 3

State of Colorado baseflows

For its Colorado River Water Availability Study using StateMod, a water allocation and accounting model (Colorado Water Conservation Board 2012), the State of Colorado developed historical monthly “baseflows” for hundreds of inflow points from the river’s headwaters in Colorado to the Colorado-Utah state line. StateMod’s baseflows represent flows that have been adjusted for upstream human effects, that is, historical gage observations are adjusted for diversions, reservoir operations, estimated consumptive uses, and return flows. Baseflows calculated at gage locations are distributed to upstream, ungaged reaches and locations.

UCRC virgin flows

The UCRC publishes current and historical total annual “virgin flows” at Lee Ferry, the Colorado River Compact point below the USGS Lees Ferry gage and below the Colorado River confluence with the Paria River, in its annual reports (UCRC 2017, 2018). The UCRC defines virgin flow as “the estimated flow of the stream if it were in its natural state and unaffected by the activities of man.”

Specifics of the UCRC calculation methods were not available, but presumably they are very similar to the methods used by Reclamation, described in the next section. Figure 5.17 shows a comparison of the UCRC and USBR virgin and natural flows at Lee Ferry and Lees Ferry, respectively. The agencies' flows will differ slightly because of their different locations relative to the mouth of the Paria River (discharge of 20 kaf/yr on average). However, the difference between the two records is not consistently signed negative, as one would expect, and is frequently on the order of hundreds of thousands of acre-feet. For most of the historical record, there is insufficient documentation on the development of the two entities' flows to understand the differences; however, data sources are available from Reclamation and the UCRC for the more recent 1988–2017 period if comparison were to be pursued. The lesson from the differences is that there may be uncertainties in the naturalization process that propagate to the naturalized streamflow values, above and beyond the uncertainties in the underlying gaged record.

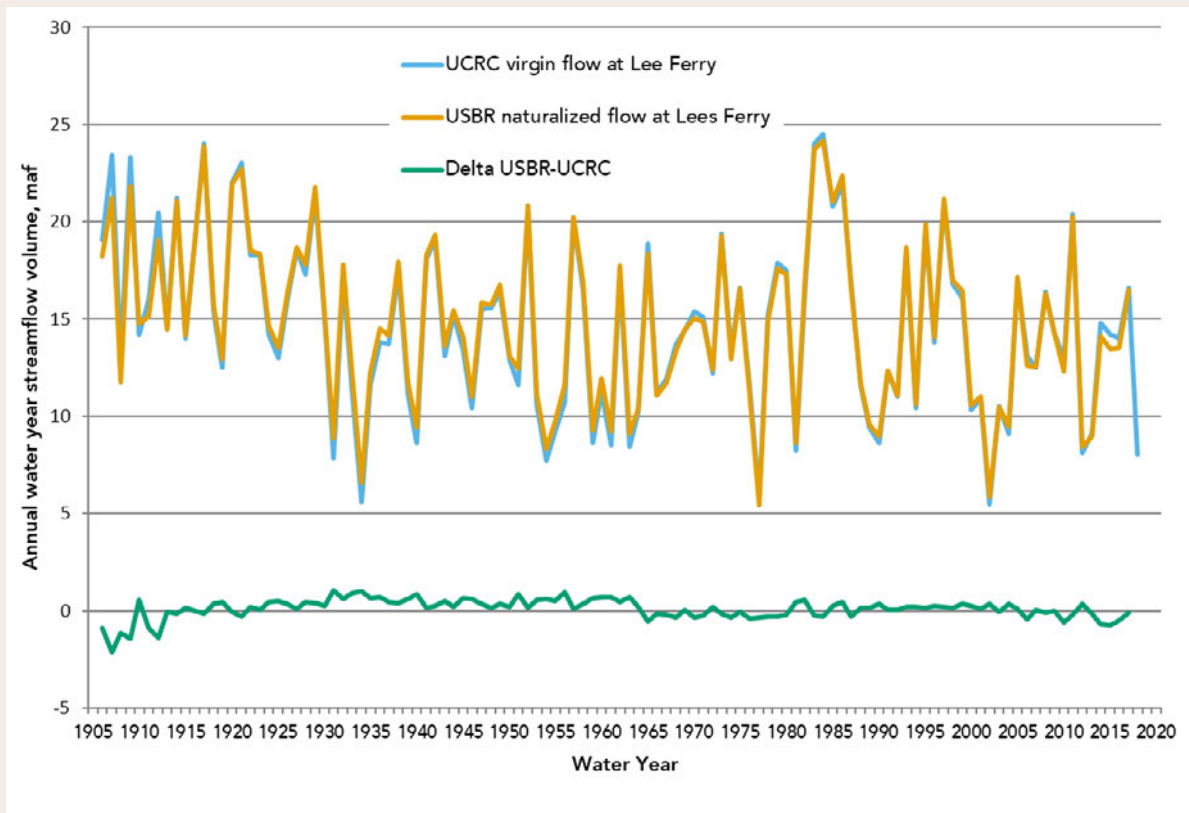


Figure 5.17

Comparison of USBR and UCRC water-year annual naturalized flows at Lees Ferry and Lee Ferry, respectively, 1906–2016. (Data: UCRC 2017, 2018; Reclamation 2019d)

Reclamation natural flows

As the key inputs to its CRSS model, Reclamation produces historical monthly “natural flows” at each of the 29 inflow points listed on Figure 5.16. The names and record lengths for the numbered locations are provided in Figure 5.15. The natural flow dataset, available on the Reclamation [website](#), is actively maintained and updated with recent natural flow values once all of the components have been compiled and adjustments made (about 12 months after the end of the year). In addition to adding to the natural flow record as each year’s data becomes available, Reclamation also frequently refines its natural flow calculations using new information and methods. These calculations and refinements are described in more detail in the next section.

To develop the monthly natural flows that are input to CRSS, Reclamation adjusts gaged streamflow data at all 29 inflow points for reservoir operations and consumptive use. The specific adjustments made to calculate natural flow for Upper Basin locations differ from those of the Lower Basin. The following summary of Reclamation’s adjustments to the gage record draws primarily from Prairie and Callejo (2005). That document describes the natural flow calculation inputs, methods, and assumptions for what was then the 1971 to 1995 natural flow dataset. Figure 5.18, modified from that document, shows a simplified process diagram for the natural flow calculations. Natural flow calculations made prior to 1971 have not been revisited since 1983 for the Upper Basin, and 1985 and 1992 for the Lower Basin, with the exception of the record extension described later in this section.

USBR Colorado River Basin Natural Flow and Salt Data

Link:
<https://www.usbr.gov/lc/region/g4000/NaturalFlow/>

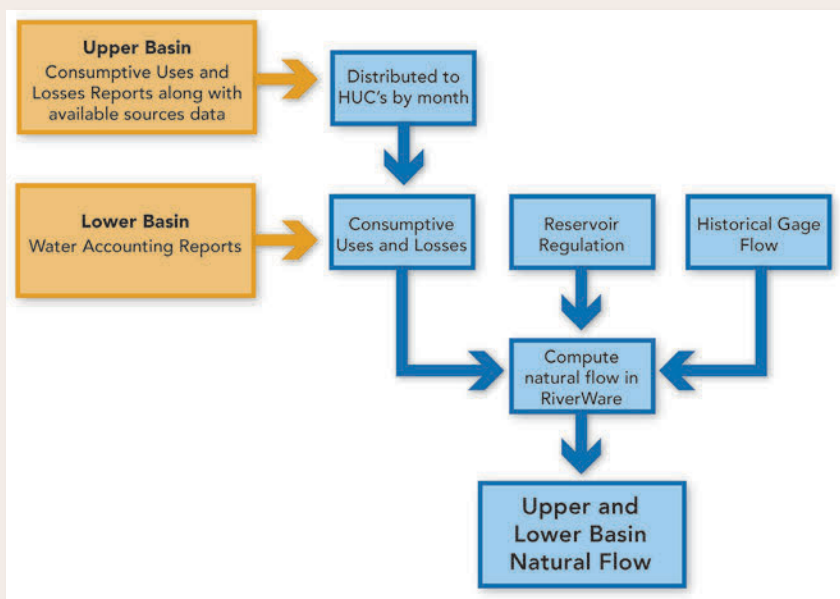


Figure 5.18

Reclamation's natural flow calculation method, as applied to gaged data from 1971 onward (Source: adapted from Prairie and Callejo 2005)

Upper Basin flow naturalization. For Upper Basin natural flows, Reclamation adjusts the observed gage record to account for upstream changes in reservoir storage and consumptive uses and losses at the 20 locations shown in Table 5.3.

Table 5.3

Upper Basin natural flow locations used in CRSS. (Source: USBR Colorado River Basin Natural Flow and Salt Data; J. Prairie pers. comm.)

USGS gaging station number	Station name	CRSS inflow point
Was 09072500 Current 09085100-09085000	Colorado River at Glenwood Springs, Colorado	1
09095500	Colorado River near Cameo, Colorado	2
09109000	Taylor River below Taylor Park Reservoir, Colorado	3
09124700	Gunnison River above Blue Mesa Reservoir, Colorado	4
09127800	Gunnison River at Crystal Reservoir	5
09152500	Gunnison River near Grand Junction, Colorado	6
09180000	Dolores River near Cisco, Utah	7
09180500	Colorado River near Cisco, Utah	8
09211200	Green River below Fontenelle Reservoir, Wyoming	9
09217000	Green River near Green River, Wyoming	10
09234500	Green River near Greendale, Utah	11
09251000	Yampa River near Maybell, Colorado	12
09260000	Little Snake River near Lily, Colorado	13
09302000	Duchesne River near Randlett, Utah	14
09306500	White River near Watson, Utah	15
09315000	Green River at Green River, Utah	16
09328500	San Rafael River near Green River, Utah	17
09355500	San Juan River near Archuleta, New Mexico	18
09379500	San Juan River near Bluff, Utah	19
09380000	Colorado River at Lees Ferry, Arizona	20

Reclamation considers two sets of reservoirs in its Upper Basin natural flow adjustments: the eight Upper Basin mainstem reservoirs explicitly represented in CRSS, and eighteen non-mainstem reservoirs not represented in CRSS. For the former, historical pool elevation data are used to determine changes in storage for adjustment of downstream natural flows. For the latter, historical monthly change in storage is used. Natural flows below Flaming Gorge Reservoir and Lake Powell include additional adjustments for changes in bank storage.

Adjustments for consumptive uses and losses (CUL) include reservoir evaporation, stock pond and livestock uses, thermal power, minerals, M&I, exports and imports, and irrigated agriculture. Reservoir evaporation is calculated from historical surface area for 42 major reservoirs and from an estimated “fullness factor” for minor reservoirs, with net evaporation rates from NOAA “Annual FWS Evaporation Atlas.” Consumptive uses and losses from historical M&I, minerals, and measured imports and exports are taken from USGS reports and communications. Losses from sublimation and evapotranspiration (ET) from non-irrigated lands are not factored into natural flow calculations.

Reclamation calculates historical Upper Basin irrigated agriculture consumptive use with the modified Blaney-Criddle ET estimation method, in combination with data on temperature, crop types, and acreage. However, because of better availability of a wider range of weather data (see Chapter 4), the modified Blaney-Criddle method may be phased out; the more fully physical Penman-Monteith method is now the preferred approach (Sammis, Wang, and Miller 2011; Technical Committee on Standardization of Reference Evapotranspiration 2005). In cooperation with, and pending approval from, the UCRC and the Upper Basin states, Reclamation may replace modified Blaney-Criddle-derived estimates of consumptive use with Penman-Monteith-derived estimates in its natural flow calculations (J. Prairie, pers. comm.).

Reclamation routinely refines the natural flow calculations. Updates to the natural flows are issued approximately annually and each update may reflect multiple refinements. The refinements fall into three categories corresponding to the data sets needed to compute natural flow: CUL data, reservoir regulation (change in storage) data, and USGS gage data. Reclamation provided several years of documented updates—three examples taken from the documentation are provided in Figure 5.19.

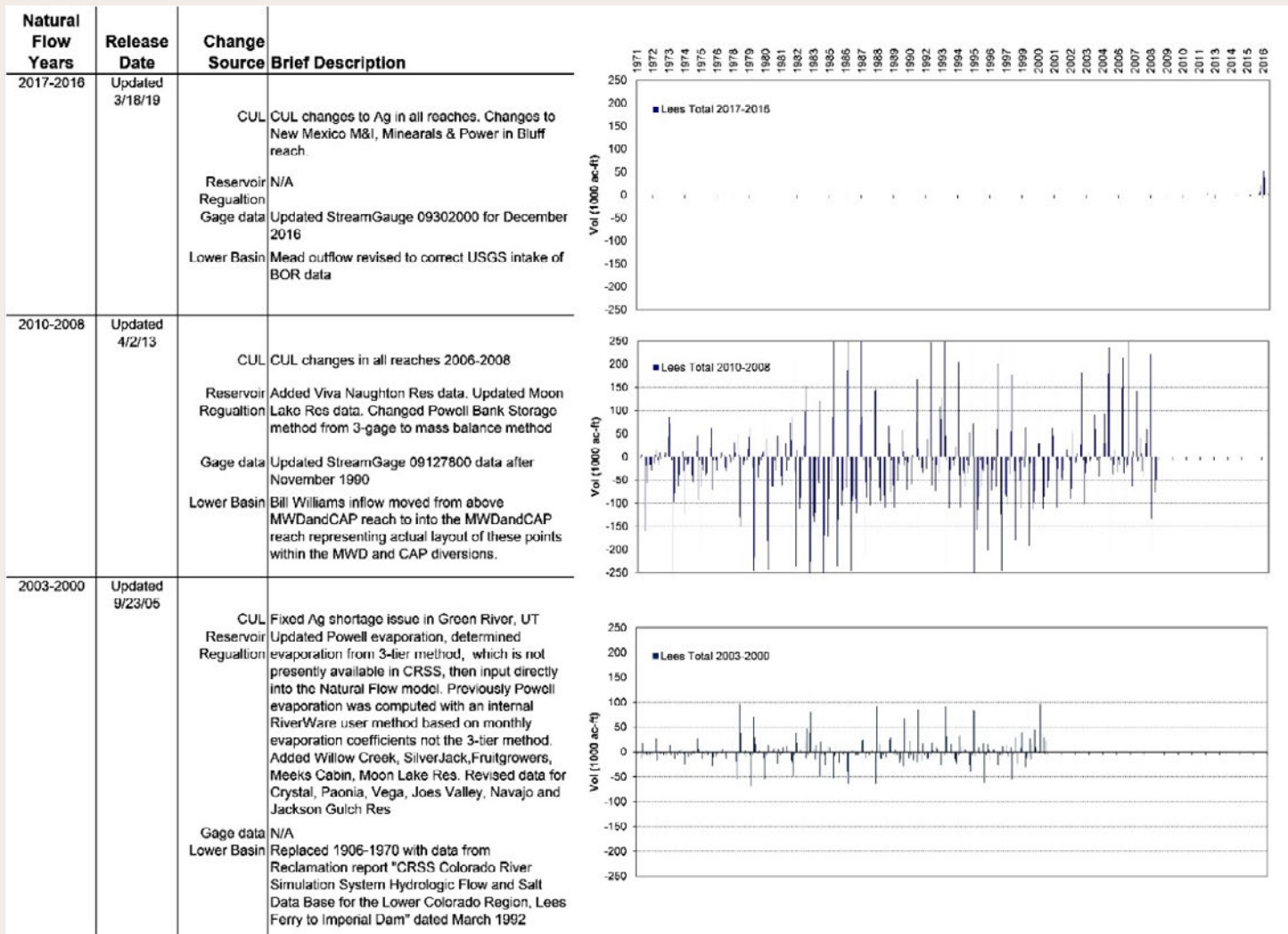


Figure 5.19

Three examples of Reclamation’s Upper Basin natural flow updates. Reclamation’s documentation of natural flow refinements summarizes the changes to each natural flow component and includes a figure with the total monthly change in natural flow at Lees Ferry since the previous update. (Source: Reclamation)

For nearly all gages, and for nearly all years, the sum of the adjustments made to naturalize the observed record are positive (i.e., adding flow back in), resulting in a natural flow record that exceeds the historical gage record. However, at the Lees Ferry gage, in extremely dry years like 1977 and 2002 (Figure 5.20), the natural flow for the entire Upper Basin (5.4 and 5.9 maf, respectively) can be less than the Lake Powell release (typically 8.2 maf), revealing a net negative adjustment to the gaged value.

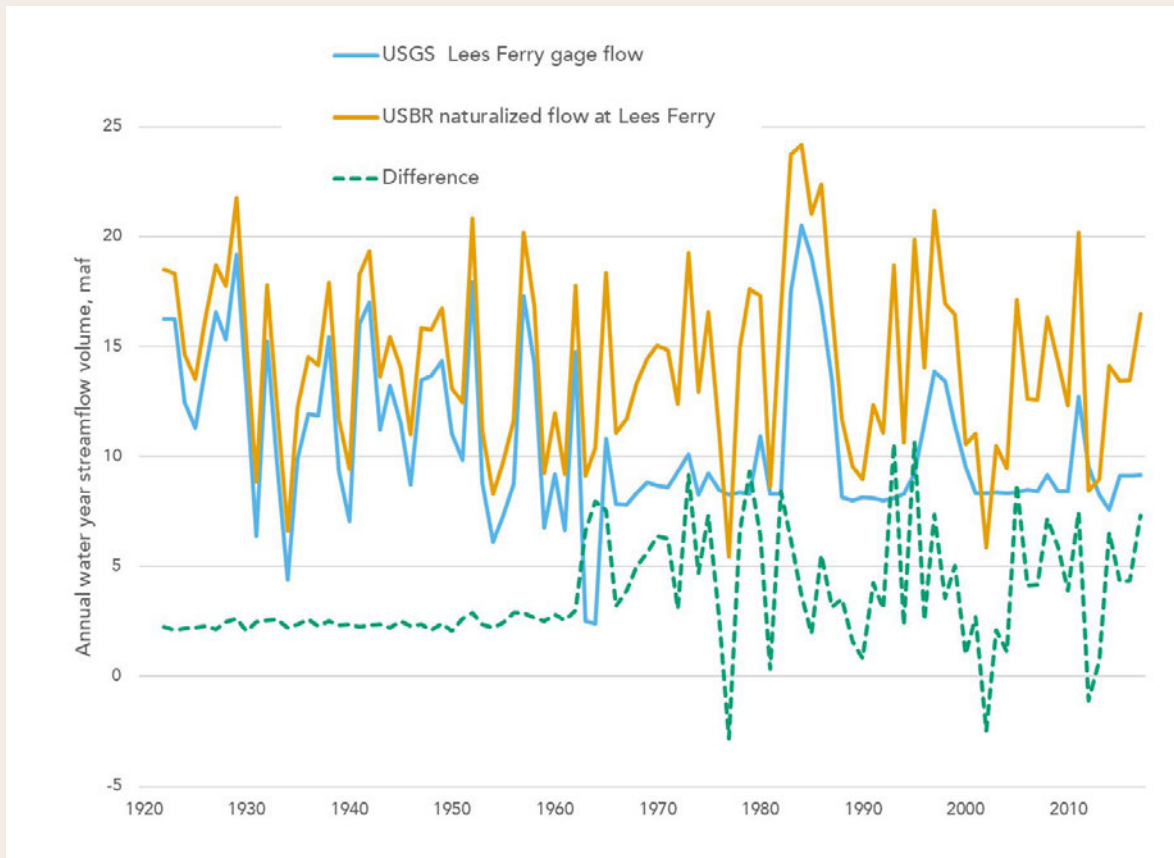


Figure 5.20

Comparison of naturalized and gaged water-year flows at Lees Ferry, 1922-2017 (Data: USGS and Reclamation)

Lower Basin flow naturalization. The basin map in Figure 5.16 shows 9 inflow points for CRSS in the Lower Basin. Five of these points are located in reaches along the mainstem, and are considered naturalized flows, and four represent tributaries. The methods for calculating CRSS inflows differ between these two types of Lower Basin inflow points.

The five Lower Basin reaches and the USGS gages (natural flow calculation points) at the downstream ends of them are shown in Table 5.4. Reclamation’s Lower Basin natural flows contain adjustments for operations at Lakes Mead, Mohave, and Havasu, and include estimates of changes in bank storage for Lake Mead.

Table 5.4

Lower Basin natural flow locations (Source: Prairie and Callejo 2005)

USGS gaging station number	Station name	CRSS inflow point	Reach name
09402500	Colorado River near Grand Canyon, AZ	23	Lees Ferry to Grand Canyon
09421500	Colorado River below Hoover Dam, AZ-NV	25	Grand Canyon to Hoover Dam
09423000	Colorado River below Davis Dam, AZ-NV	26	Hoover Dam to Davis Dam
09427520	Colorado River below Parker Dam, AZ-CA	28	Davis Dam to Parker Dam
09429490	Colorado River above Imperial Dam, AZ-CA	29	Parker Dam to Imperial Dam

The method for estimating consumptive uses and losses for these reaches is different from that in the Upper Basin. Rather than calculate historical consumptive use from acreage and ET estimates, Reclamation relies on water use records from Decree Accounting, recently renamed Water Accounting, reports (Reclamation 2016c) that are compiled in accordance with the court decree in *Arizona v California*. In total, consumptive uses from 52 diversions are accounted for in the Lower Basin natural flow calculations. However, according to Prairie and Callejo (2005), for some diversions, the consumptive use is modified by an “unmeasured returns” factor that reduces the depletion.

Reservoir evaporation is estimated with monthly evaporation coefficients and surface areas for lakes Mead, Mohave, and Havasu.

Lower Basin natural flows are also adjusted to reflect the impact of phreatophytes. Monthly average consumptive use by phreatophytes for two reaches, Davis to Parker and Parker to Imperial, which sum to over 500,000 acre-feet per year, are applied.

Natural flow is not calculated for the Lower Basin tributaries; instead, historical gage data are used for the 4 tributaries shown in Table 5.5, with the corresponding gaging station. As described in Chapter 3, the Gila River is not represented in CRSS.

Table 5.5

Lower Basin tributaries represented in CRSS. (Source: Prairie and Callejo 2005)

USGS gaging station	Station name	CRSS Inflow point
09382000	Paria River At Lees Ferry, AZ	21
09402000	Little Colorado River Near Cameron, AZ	22
09415000	Virgin R At Littlefield, AZ	24
09426000	Bill Williams River Below Alamo Dam, AZ	27

There are hydroclimatic implications to using the historical gage data at the tributaries rather than naturalizing the inflows. Lower Basin tributary gage flows are heavily modified by upstream human activity and therefore do not reflect the natural hydrologic variability of those tributaries. Efforts to analyze trends or calibrate models based on these inflows will produce misleading results, and simulations that are imposed on this already-impaired streamflow record cannot explore changes to the uses or operations on the tributaries. Reclamation is in the process of computing historical (1971-present) consumptive uses and losses for the tributaries and will ultimately compute natural flows at the four gage locations for use in CRSS (J. Prairie, pers. comm).

Natural flow record extension

The time series for observed streamflow records for the 29 key inflow points in the basin are only partially overlapping, as noted above and shown in Figure 5.15. Rather than attempt to extend the various gage records back to a common starting point and then estimate natural flows from the extended gage records, Reclamation has extended the natural flow records themselves. In 1983, Reclamation used multiple linear regression on the overlapping natural flows that had been calculated from gage records to derive equations to extend all the missing natural flows back to 1906. In 2006, taking advantage of 20 additional years of common natural flow estimates, Lee and Salas used multiple linear regression and nearest-neighbor methods to revise and update the 1983 extensions. They disaggregated the updated annual natural flows to monthly natural flows and incorporated a random error term to represent the uncertainty in the estimates (Lee and Salas 2006). Reclamation currently uses the Lee and Salas (2006) extended natural flow for all periods from 1906 until the start of the gage record at a given site.

CBRFC unregulated flows

The CBRFC forecasts monthly “unregulated flows” for basin locations corresponding to Upper Basin inflow points in Reclamation’s 24MS (9 points) and MTOM (12 points) models (see Chapter 3 for the locations and details of these inflow points). The CBRFC’s unregulated flows are gaged flows that have been adjusted for some, but not all, upstream activities, and thus are not as fully naturalized as natural or virgin flows. The CBRFC takes observed flows and removes the effects of measured upstream diversions, exports, imports, and reservoir regulation. The formula for CBRFC’s unregulated flow calculation, in which all the terms are taken from measured data, is given below and illustrated in Figure 5.21.

$$\text{Unregulated flow} = \text{Observed flow} + \text{Diversions} + \text{Exports} - \text{Imports} \pm \text{Change in Storage}$$

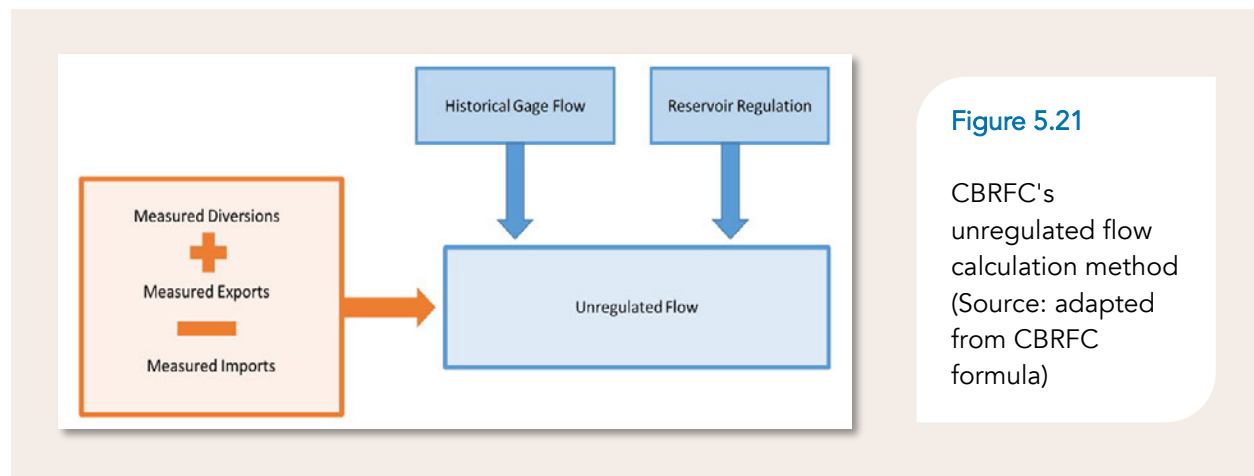


Figure 5.21

CBRFC's unregulated flow calculation method (Source: adapted from CBRFC formula)

Besides having very different applications, the primary difference between the CBRFC’s unregulated flows and Reclamation’s natural flows is the treatment of upstream diversions and return flows. Upstream activities that are either not measured or for which data is unavailable in a routine and timely manner are not backed out of the observed gage flow in the CBRFC version.

It should be noted that, for purposes besides 24MS or MTOM inputs, unmeasured depletions, such as localized irrigation, are modeled by the CBRFC to estimate how much water is applied to, consumed by, and returned from known irrigation areas, but these estimates are not used in the CBRFC’s unregulated flow calculations.

Reclamation unregulated flows

Reclamation also calculates unregulated flows, but only retrospectively (i.e., they are not used as the basis of forecasts like CBRFC's). With the exception of the inflow to Navajo Reservoir, Reclamation's unregulated flow calculations only account for the change in storage of any Reclamation reservoir directly upstream. Unregulated inflows to Navajo Reservoir are a special case because 24MS and MTOM both model projected diversions through the Azotea Tunnel, which is above the reservoir. Within Reclamation this Navajo Reservoir inflow is termed "modified unregulated" because Reclamation *does* add back in the diversions in its unregulated calculation.

Though there are minimal differences between Reclamation's and CBRFC's unregulated streamflow values at all overlapping locations, three CBRFC forecasts are adjusted based on Reclamation's calculations or needs: inflows to Powell, Flaming Gorge, and Navajo reservoirs. CBRFC's Lake Powell unregulated inflow forecast is adjusted via a linear regression to more closely match Reclamation's retrospective calculations, and this adjusted inflow becomes CBRFC's official forecast. For the inflow to Flaming Gorge, CBRFC calculates a special forecast for use in Reclamation's models that is a hybrid between regulated and unregulated: the impacts of regulation by non-Reclamation reservoirs between Fontenelle and Flaming Gorge are preserved (i.e., not backed out as in the standard unregulated calculation procedure). This is different from CBRFC's official published forecast into Flaming Gorge, which is developed as described above. The last special case is for the inflow into Navajo Reservoir. As previously described, Reclamation adjusts its unregulated calculation for the impacts of Azotea Tunnel, so this aspect of inflow to Navajo matches the CBRFC procedure and does not require any special treatment. Because there is significant irrigation activity between Vallecito Reservoir and Navajo that Reclamation does not consider in its internal unregulated calculations, CBRFC provides a hybrid forecast that includes regulation between Vallecito and Navajo so that the resulting Navajo forecast value is closer to what Reclamation produces in its retrospective calculations. This hybrid product is different from CBRFC's official, published, unregulated Navajo inflow forecast.

A comparison of Reclamation's natural flows and unregulated flows is shown in Figure 5.22. Comparison of Reclamation's and CBRFC's publicly reported April-July unregulated flows into Lake Powell over the 1964 to 2016 period show that they are almost perfectly correlated and agree, on average, within 0.02%. If the CBRFC unregulated flows for Lake Powell were plotted in Figure 5.22 they would be indistinguishable from Reclamation's unregulated inflows.

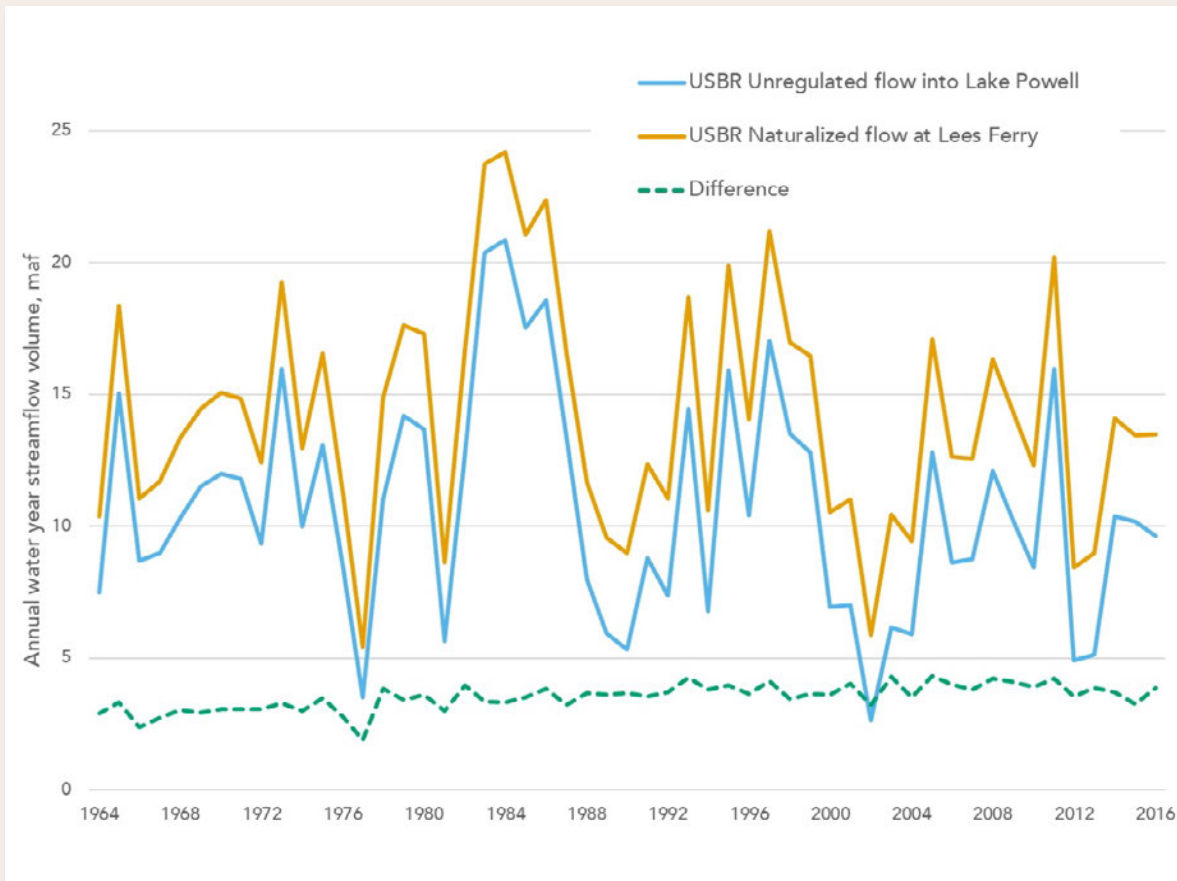


Figure 5.22

Comparison of Reclamation's water-year unregulated flows into Lake Powell with their naturalized flows at Lees Ferry, 1964–2017. (Data: Reclamation)

5.4 Soil moisture observations and monitoring

Soil moisture, like snowpack, serves as a key interface between atmospheric and hydrologic processes. It links the energy budget and water budget of a watershed by controlling whether incoming energy goes into the evaporation of moisture, or the heating of the land surface. And like snowpack, soil moisture integrates precipitation and evapotranspiration over long time periods, imparting memory to the hydrologic system (Shelton 2009).

Antecedent fall soil moisture is an important influence on runoff efficiency for the following spring, and thus a soil-moisture term is included in the CBRFC streamflow forecast model. Anomalously low antecedent soil moisture will reduce the forecasted seasonal streamflow, especially for the early season forecasts (December and January) because there is less information then about the snowpack; at those times, forecasted flows are

reduced by about 7–10% per 10% departure from normal soil moisture conditions (P. Miller, pers. comm.). Until 20 years ago, in situ observations of soil moisture in the Colorado River Basin were extremely sparse. The density of in situ soil moisture observations in the basin has increased in recent decades, but the spatial representativeness of the point observations is still problematic for basin-wide applications. Accordingly, CBRFC uses modeled soil moisture in their streamflow forecasting. CBRFC has found that only the deepest in situ soil moisture measurements, at about 1 m, correlate with their modeled soil moisture, and many in situ sites do not have sensors at that depth. New remotely sensed data on soil moisture from satellites have the potential to augment and better tie together in situ and modeled soil moisture data, though most remotely sensed data only extend through the top layer (roughly 10 cm) of soil (Table 5.6).

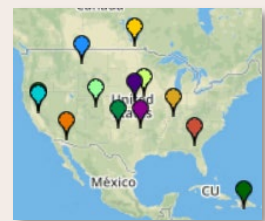
The modeling of soil moisture has a large conceptual and practical overlap with the modeling of evapotranspiration and evaporative demand (Section 5.5) since they are all terms in balancing the energy budget and water budget at the land surface.

In situ soil moisture measurements

About 100 in situ soil moisture observing sites have been established in recent years in the basin, with most of them located in the Upper Basin (Figure 5.23). By far, the greatest number of these are at SNOTEL sites, with some of them having records going back to early 2000s. Other networks that host multiple soil-moisture sites in the basin include the Soil Climate Analysis Network (SCAN), U.S. Climate Reference Network (USCRN) and the Interactive Roaring Fork Observing Network (iRON) in central Colorado. Each site provides measurements of soil moisture at multiple depths from 5 cm (2") up to 1 m (39"), depending on the network.

Outside of the SNOTEL network, which covers the high-elevation regions in the Upper Colorado River Basin, the in situ monitoring is still very sparse, and may not adequately assess the conditions (and water demand) from the lower-elevation, more arid part of the basin. Real-time data and historical data from all of these networks and stations can be accessed from the [National Soil Moisture Network](#) (NSMN) or the [International Soil Moisture Network](#) (Dorigo et al. 2011).

International Soil Moisture Network



Link:
https://www.geo.tuwien.ac.at/insitu/data_view er/

Table 5.6

Summary of characteristics of in situ, remotely sensed, and modeled soil-moisture (SM) data available for the Colorado River Basin. See the text for further description of most of these networks/products.

Network or Product Name	Method	Soil Moisture (SM) Variables	Spatial Resolution or Number of Stations	Spatial Coverage	Temporal Resolution
National Soil Moisture Network	In situ Observations	SM at multiple depths (5-100 cm)	~1000 stations from multiple networks	CONUS	daily
NLDAS-2	Land Surface Modeling	SM at multiple depths (10-100 cm)	12 km	CONUS	daily
SMAP	Remote Sensing	0-5 cm SM	36km	Global	2-3 days
SMOS	Remote Sensing	0-5 cm SM	50km	Global	3 days
LIS (Noah Model + SMAP)	Remote Sensing + Land Surface Model	0-10, 10-40, 40-100 and 100-200 cm SM	3 km	CONUS	daily
ESI	Remote Sensing + Energy Balance Model	Root zone SM in percentiles	4 km	CONUS	monthly composite
LERI	Remote Sensing + Energy Balance Model	Root zone SM in percentiles	1 km	CONUS	monthly and 8-day
GRACE-DA-DM	Remote Sensing + Land Surface Model	Groundwater, root zone SM and surface SM percentiles	12 km	North America	weekly

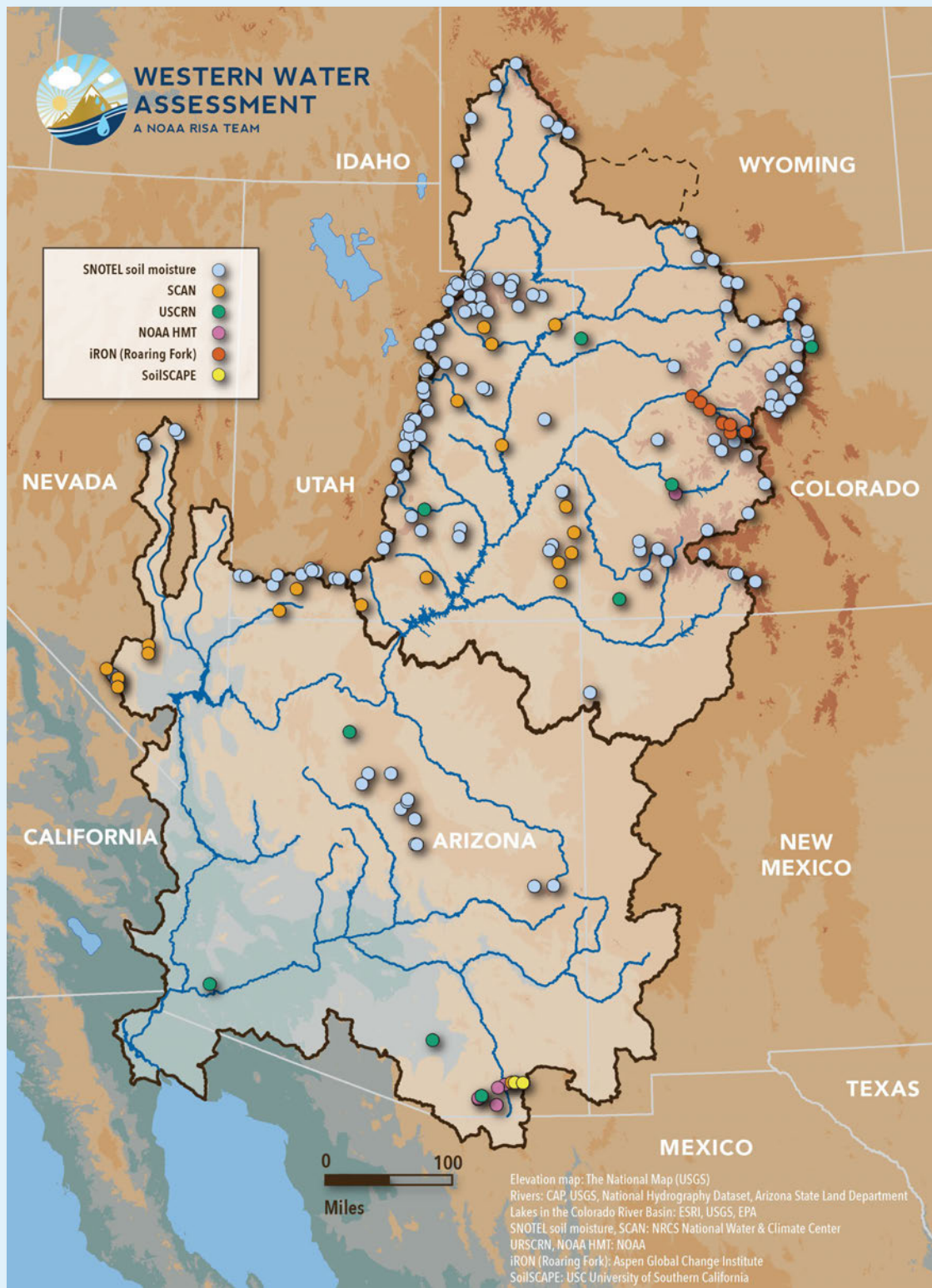


Figure 5.23

Locations of in situ soil moisture monitoring sites that are part of the National Soil Moisture Network (NSMN). (Source: NSMN; <http://nationalsoilmoisture.com/>)

Modeled soil moisture

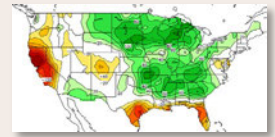
Because of the scarcity of both in situ and remotely sensed soil moisture data, real-time soil moisture conditions have generally been modeled, using observed meteorological inputs—primarily temperature and precipitation, but also humidity and solar radiation in some cases.

Hydrologic models used to model soil moisture have been either simple bucket models, as in the case of NOAA's Climate Prediction Center's Soil Moisture [product](#) (Huang, Van den Dool, and Georgarakos 1995), or more complex land surface models as the NLDAS-2 Drought Monitor Soil Moisture online [products](#) (VIC, MOSAIC, Sac-SMA and NOAH models; Schaake et al. 2004) and UCLA's Experimental Surface Water [Monitor](#) (VIC model; Wood 2008). Modeled estimates of soil moisture are typically made for the total moisture in the whole soil column and do not have explicit information on moisture conditions at particular depths. This poses a challenge to efforts to blend the modeled total-column estimates with the depth-specific in situ observations, such as the National Soil Moisture Network blends described below.

The CBRFC models soil moisture as part of their streamflow forecast procedure using the Sac-SMA model (Sacramento–Soil Moisture Accounting, see Chapter 6). Sac-SMA divides the soil response into a fast-responding upper zone (approximately the top 20–50 mm of soil) and a slower-responding lower zone (generally deeper than 50 mm). In the model, a basin's antecedent condition prior to snowmelt, i.e., the lower zone soil moisture, influences the forecasted volume of runoff during the spring and summer months. As with the Snow-17 model, the Sac-SMA model is run in a lumped framework, in which individual watersheds are divided into up to three elevation zones, depending on the amount of relief within the basin, vegetation patterns, and snowpack patterns. Sac-SMA model parameters, including those that govern soil moisture processes, are defined separately for each elevation zone within each watershed. The CBRFC has examined incorporating in situ observed soil moisture data into their model but has found that these data were not appropriate for the CBRFC's modeling environment (P. Miller, pers. comm.).

Modeled soil moisture provides much more spatially distributed information than point in situ observations; however, the modeled data also inherit the uncertainties in the underlying meteorological observations, particularly precipitation (Chapter 4), as well as uncertainties in the parameterization of soil and vegetation properties that influence the translation of precipitation into soil moisture.

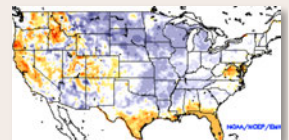
NOAA Soil Moisture



Link:

https://www.cpc.ncep.noaa.gov/products/Soil_mst_Monitoring/US/Soilmst/Soilmst.shtml

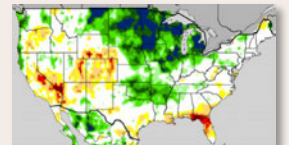
NLDAS Soil Moisture



Link:

<https://www.emc.ncep.noaa.gov/mmb/nldas/drought/>

UCLA Soil Moisture



Link:

<http://www.hydro.ucla.edu/SurfaceWaterGroup/forecast/monitor/index.shtml>

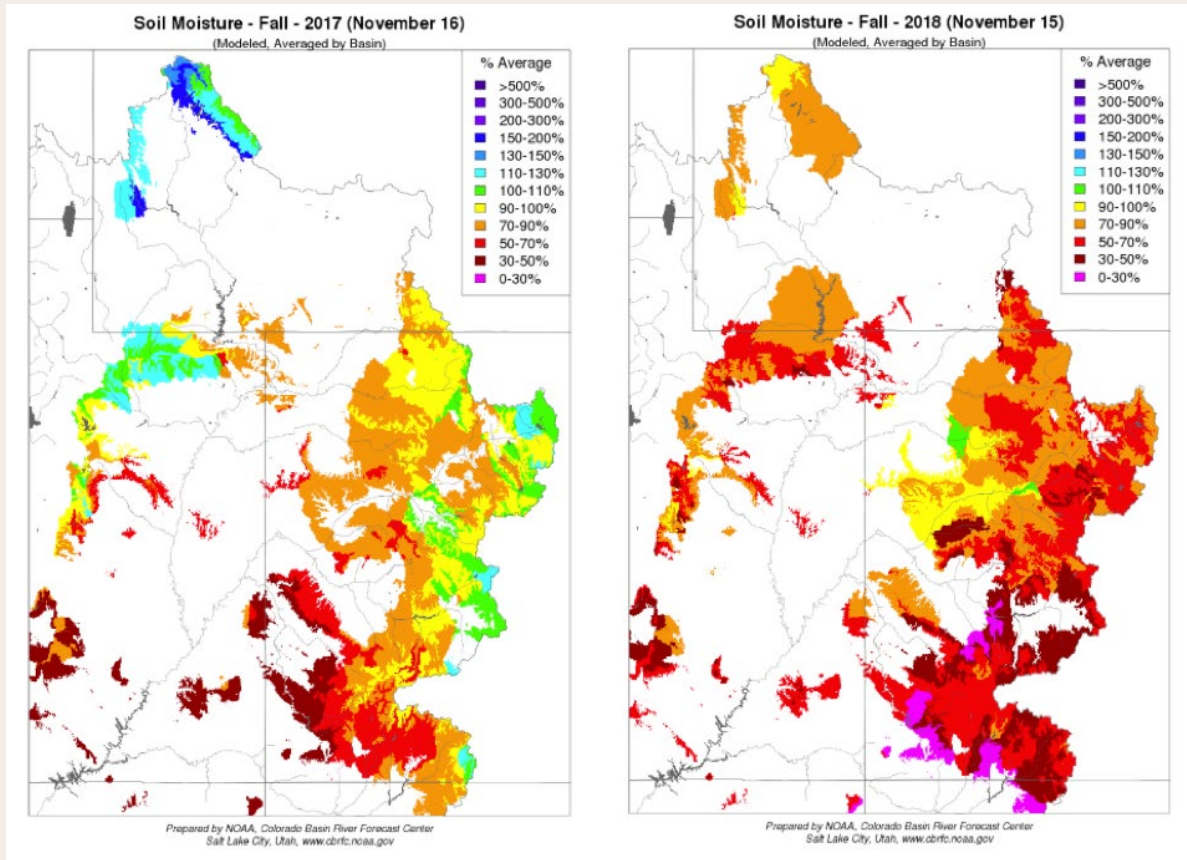


Figure 5.24

CBRFC operational modeled soil-moisture conditions (% of average) for mid-November 2017 (left) and 2018 (right). The mid-November time frame is indicative of the antecedent soil moisture that influences the efficiency of the spring runoff. The CBRFC soil moisture model is “lumped” or “partially distributed,” meaning that conditions are estimated for each model unit (multiple elevation zones in each watershed), but not on a gridded, pixel-by-pixel basis. (Source: CBRFC; https://www.cbrfc.noaa.gov/wsup/sac_sm/sac_sm.php)

Remotely sensed soil moisture

Satellite-based data have become increasingly available in recent years to assess soil moisture, through retrieval of soil moisture’s signature in microwave-band radiation reflections and scatter, or by assimilating satellite observations of various surface properties in a land surface/hydrology model to model soil moisture. While satellite retrievals of soil moisture are generally restricted to the upper 10 cm of soil, as mentioned earlier, the assimilation of satellite data into modeled soil moisture can usefully inform estimates at much greater depths (>100 cm), since soil moisture anomalies tend to propagate downward in the soil column over time (Kumar et al. 2019). The CBRFC has not yet evaluated the potential to incorporate remotely sensed soil-moisture data in their forecast model.

NASA's Soil Moisture Active Passive (SMAP) satellite was launched in 2015 to retrieve the soil moisture signal in microwave-band radiation. Because of the failure of the radar (the active sensor), only the radiometer (the passive sensor) data is available. The passive sensor provides an assessment of the near-surface soil moisture (upper 5 cm) and a spatial resolution of 36 km every 2-3 days and is available on a SMAP [webpage](#). SMAP radiometer observations have also been combined with Sentinel-1 satellite radar (i.e., active) observations to estimate soil moisture at a much higher spatial resolution (3 km); a near real-time Beta-release version of this data is currently available [online](#) for monitoring applications with a 2-day lag time (Das et al. 2018). NASA's Short-term Prediction Research and Transition (SPoRT) Center provides real-time output of soil moisture [variables](#) every hour for CONUS at 3 km resolution by assimilating SMAP observations in the Noah land-surface/hydrology model (Blankenship et al. 2018).

The European Space Agency's Soil Moisture and Ocean Salinity (SMOS) mission was launched in 2009. Similar to SMAP, SMOS provides estimates of soil moisture in the top 5 cm at a spatial resolution of 50 km every 3 days. One study has shown that both SMAP and SMOS products have a dry bias in a topographically complex mountain region in China (Zhang et al. 2019), but it is not clear whether this is true for other mountain regions.

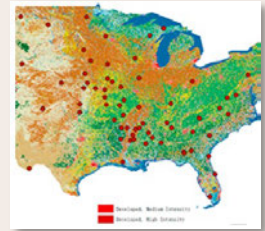
Root zone soil moisture can also be assessed using other satellite derived products that use remotely sensed "land skin" temperature and an energy-balance model to assess the evaporative response from land. The Evaporative Stress Index (ESI; Anderson et al. 2011) is a 4-km spatial resolution data [product](#) based on GOES satellite data, available as a monthly composite updated with 1-day latency between late March and early October. ESI has been shown to be a useful predictor of agricultural yield anomalies and other vegetation impacts caused by soil-moisture drought stress (Hobbins, McEvoy, and Hain 2017)

A newer, similar product is the Landscape Evaporative Response Index (LERI; Rangwala et al. 2019), which is a 1-km spatial resolution dataset derived from Simplified Surface Energy Balance (SSEBop) evapotranspiration data that incorporates MODIS Terra observations and is available [online](#) at multiple timescales of integration with a lag time of 1-2 weeks.

National Soil Moisture Network

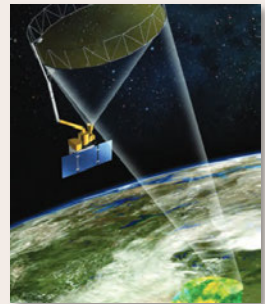
The National Soil Moisture Network (NSMN) is an ongoing multi-agency and multi-university effort that aims to integrate soil moisture data from the several existing in situ monitoring networks throughout the United States, and also to merge these data with modeled and remotely sensed soil moisture products to generate near real-time, high-resolution, gridded national soil moisture maps and other products (Clayton et al. 2019).

NASA SMAP Data



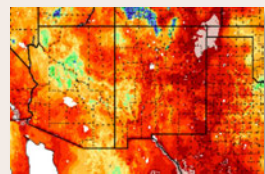
Link:
<https://nsidc.org/data/smap/smap-data.html>

SMAP Sentinel-1



Link:
https://nsidc.org/data/SPL2SMAP_S/versions/2

NASA SPoRT Center



Link:
https://weather.msfc.nasa.gov/sport/case_studies/lissmapda_CONUS.html

Currently, the NSMN [website](#) provides three types of soil moisture map products for the U.S.: 1) interpolated in situ observations of soil moisture, including an interpolation scheme (regression kriging) that uses PRISM precipitation; 2) a blend of the regression-kriging interpolated in situ map with NLDAS modeled soil moisture, and 3) a blend of 2) and a SMAP passive-radiometer remotely sensed soil moisture product. The NSMN also provides daily soil-moisture data from all in situ networks, but the data archive only extends back to August 2018.

5.5 Evaporation, evapotranspiration, and evaporative demand

To support a variety of water resource management decisions, estimates of open-water evaporation, evapotranspiration (ET), and evaporative demand are required at varying timescales: daily (reservoir operations), weekly (irrigation scheduling), and seasonally (demand and consumptive use estimation) (Hobbins and Huntington 2017). Estimates of watershed-scale evapotranspiration are also used to validate the simulated water budget in hydrologic models, including that used by the CBRFC for streamflow forecasting. Estimates of monthly reservoir evaporation and consumptive use by agriculture are also important terms in the Reclamation operations and planning models and in their flow naturalization calculations.

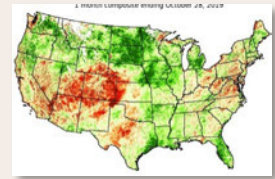
Generally, evaporation-related variables are estimated using a model driven by meteorological observations, or are derived from remote sensing data. Direct in situ observations of these variables (e.g., pan evaporation) are very sparse and do not offer an adequate spatial representation at the watershed or basin scale.

Monitoring of open-water evaporation

Open water evaporation in a large reservoir setting is notoriously difficult to quantify; many different methods have been used to estimate open water evaporation, each with benefits and challenges for operational use, as summarized by Friedrich et al. (2018). Historically, pan evaporation has often been used by water managers as a proxy for reservoir evaporation, including at Lake Powell in the late 1950s, but this method can produce large errors in both the amount and seasonal timing of evaporation (Friedrich et al. 2018).

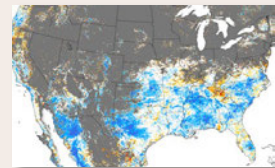
The bulk aerodynamic, or mass transfer, method is arguably the most cost-effective approach for near real-time operational monitoring. From 1955–1994, the USGS calculated evaporation at Lake Mead using the mass transfer method, and from 1965–1979, Reclamation calculated evaporation at Lake Powell using the mass transfer method (Reclamation 1986). The average monthly evaporation from these deployments of the mass transfer method have been incorporated into the 24MS model as static coefficients

USDA Evaporative Stress Index



Link:
<https://hrsl.ba.ars.usda.gov/drought/index.php>

Landscape Evaporative Response Index



Link:
<https://www.esrl.noaa.gov/psd/leri/>

National Soil Moisture Network



Link:
<http://nationalsoilmoisture.com/>

for modeling reservoir evaporation. However, comparison with newer techniques has shown that the mass transfer method likely has consistent biases (Moreo and Swancar 2013).

The Eddy Covariance (EC) method is regarded as the most direct and accurate approach to quantifying open water evaporation, if properly instrumented and calibrated (Hobbins and Huntington 2017). This method has been shown to have high accuracy in estimating evaporation from Lake Mead, with estimated uncertainties of 5–7% or less (Moreo and Swancar 2013).

A major advantage of the EC method is the ability to accurately quantify daily and sub-daily evaporation. However, this method has substantial instrumentation and data processing requirements that limit its application more widely (Friedrich et al. 2018). Another relatively accurate approach is the Bowen Ratio Energy Balance (BREB) method. But this method requires accurate estimates of the reservoir heat storage term, which varies considerably, and is therefore considered more appropriate for applications over longer timescales, i.e., weeks to months (Moreo and Swancar 2013; Friedrich et al. 2018).

The Penman–Monteith method, which uses a suite of climate variables as input to estimate evapotranspiration, has been modified to estimate open water evaporation and can compute annual fluxes within 5% accuracy (Finch 2001; Jensen, Dotan, and Sanford 2005; Harwell 2012). The accuracy, however, is lower at finer temporal scales, e.g., the daily or monthly inputs needed for most water system modeling.

Since 2010, the USGS and Reclamation have partnered to produce real-time evaporation estimates for Lake Mead and Lake Mojave using the EC and BREB methods (Moreo and Swancar 2013) with the goal of generating a continuous record from 2010–2019. A final report is expected in 2020. The results will be used to revise projections of future evaporation for use in system modeling. Also, as of 2019, Reclamation is partnering with the Desert Research Institute (DRI) to calculate and compare evaporation estimates for Lake Powell using the EC, BREB, and mass transfer methods at the same floating observation site (Figure 5.25). This effort will try to establish which method or methods have the greatest potential for long-term operational monitoring, given accuracy, cost, and other considerations.



Figure 5.25

Evaporation monitoring platform located in Padre Bay at Lake Powell, part of a joint study between Reclamation and the Desert Research Institute (DRI). Sensors measuring wind speed and other weather parameters along with water temperature will allow intercomparison of multiple methods for estimating reservoir evaporation. (Image: DRI.)

Monitoring of evapotranspiration

Evapotranspiration (ET) refers to aggregate loss of water from the land surface: evaporation from soils, open water, and snow and ice, and transpiration from plants. Actual ET (AET) is the real loss of water from the land surface, while potential ET (PET) refers to the water loss that *would* occur if the water supply at the land surface were unlimited. In the following discussion, ET is used to mean AET. The robust estimation of ET losses from irrigated lands is central to consumptive use (CU) estimates used in system modeling and planning. Direct in situ measurements of ET, such as the Eddy Covariance method described above, are relatively sparse and do not provide an adequate spatial representation across a landscape or basin, though they are critical for validating estimates from other methods.

More frequently, ET is estimated using one of several indirect methods described in more detail below, including 1) estimation of a reference crop evapotranspiration based on meteorological inputs and relevant crop coefficients, appropriate for irrigated land only, 2) using a land-surface/hydrology model with meteorological inputs, and 3) using satellite observations of land-surface temperature in an energy balance model. The accurate estimation of ET losses at the landscape/basin scale remains a major challenge (Amatya et al. 2016).

Table 5.7

Summary of evapotranspiration and evaporative demand data available over some or all of the Colorado River Basin. See the text for further description of most of these networks and products.

Network or Product Name	Method	Variables	Spatial Resolution or # Stations	Spatial Coverage	Temporal Resolution
CoAgMET (CO Climate Center)	Reference ET formulation incorporating weather obs	Reference ET	> 100 stations	Colorado	daily
NICE Net (DRI)	Reference ET formulation incorporating weather obs	Reference ET	18 stations	Nevada	daily
AZMET (U. of Arizona)	Reference ET formulation incorporating weather obs	Reference ET	29 stations	Arizona	daily
AgriMet (Reclamation and partners)	Reference ET formulation incorporating weather obs	Reference ET	~ 300 stations (includes CoAgMet, NICE Net, Utah AgWx stations)	Western US	daily
Utah AgWx (Utah Climate Center)	Reference ET formulation incorporating weather obs	Reference ET	~ 40 stations	Utah and western Wyoming	daily
Ameriflux (LBNL and partners)	In situ measurement based on Eddy Covariance	Actual ET	> 400 stations (20 within CRB)	North and South America	30 min to daily
NLDAS-2	Land Surface Modeling	Actual ET	12 km	CONUS	daily
SSEBop	Remote Sensing + Energy Balance Model	Actual ET	1 km	CONUS	8-day
ALEXI ET	Remote Sensing + Energy Balance Model	Actual ET	8 km	CONUS	daily
EDDI	Reference ET formulation incorporating gridded weather obs	Evaporative Demand	12 km	CONUS	daily

Reference crop ET estimations

Reference ET or reference crop ET (ET_0) is an estimate of the upper bound of ET losses from irrigated croplands given a specific crop type, and thereby the water needed for irrigation, and not actual water fluxes from the land (i.e., AET). Traditionally, the Blaney-Criddle method has been used to estimate reference ET, but the tradeoff for its simple requirements for meteorological input—temperature only—is highly inaccurate estimates under many conditions (URS 2013). More physically based formulations of Reference ET, such as Hargreaves and Penman-Monteith, require more meteorological inputs—maximum and minimum temperatures, humidity, solar radiation, and wind speed—and, as with Blaney-Criddle, a specific crop ET coefficient (Allen et al. 1998). Real-time daily estimates of Reference ET for 10 different crop types are available from the CoAgMET [network](#) for more than 100 locations across Colorado. Several other networks—AZMET, NICE Net, Utah AgWx, Agrimet—also provide real-time daily estimates of Reference ET (Table 5.7). Spatially gridded data for reference ET (e.g., ASCE Grass or Alfalfa Reference ET) are also computed in near real-time using different gridded climate datasets and are accessible through [Climate Engine](#).

Land surface modeling

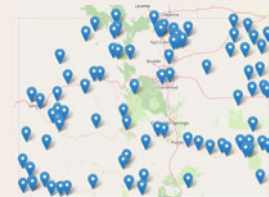
Real-time and gridded ET (AET) estimates are also available from land surface/hydrology models that are driven by observed meteorological forcings. The North American Land Data Assimilation System Phase 2 (NLDAS-2) project provides ET data at hourly or daily timescales at 12 km (7 mile) spatial resolution for CONUS from four different models: Mosaic, Noah-2.8, SAC, and VIC-4.0.3 (Xia et al. 2012). These models generally do not incorporate observations of irrigation water use. Uncertainties in soil and vegetation characteristics, and in climate at finer spatial scales, can also significantly influence the model output. Different models driven by identical climate inputs will result in different outputs.

Remote sensing

Optical and thermal imagery from satellites have become important datasets in recent years for estimating ET from field to landscape scales with a temporal resolution from days to weeks (Hobbins and Huntington 2017). Near real-time ET (AET) datasets from remotely sensed data include:

- **SSEBop ET:** This estimate of ET is based on a thermal index approach that integrates satellite observations (MODIS, Landsat) of land skin temperature (at about 5 cm depth) and gridded climatological observations of air temperature (e.g., PRISM) by using the SSEBop model (Senay et al. 2007). The MODIS-based ET product (1-km resolution) is [available](#) in near real-time (every 8 days) during the growing season (April–October). A monthly ET product is also available throughout the year.

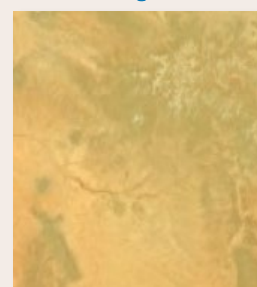
CoAgMET



Link:

<https://coagmet.colostate.edu/>

Climate Engine



Link:

<https://app.climateengine.org/climateEngine>

US SSEBop Evapotranspiration



Link:

<https://earlywarning.usgs.gov/ssebop/modis>

- **METRIC:** This method likewise uses satellite data (Landsat; 30-m resolution) in an energy balance model to compute and map ET (Allen, Tasumi, and Trezza 2007). METRIC calculates ET as a residual of the surface energy balance. METRIC is currently used by all four Upper Basin states and Reclamation for monitoring ET.
- **ALEXI ET:** The Atmosphere–Land Exchange Inversion model also estimates ET using an energy–balance model (Anderson et al. 1997). It exploits the daily observations of land skin temperature from the NOAA GOES satellite to deduce land surface fluxes, including ET. These ET data are available daily at an 8-km spatial resolution.

Efforts to improve ET estimation in the Colorado River Basin and the West

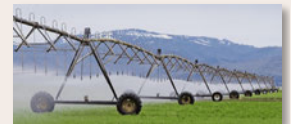
The Upper Colorado River Commission, the four Upper Division states (Wyoming, Colorado, Utah, and New Mexico), and Reclamation have sponsored a multi-year study, currently in its third phase, to assess and improve determinations of consumptive use from agriculture. The study is reviewing the different methods used by the four states and Reclamation to estimate ET, including newer remote sensing-based methods (SSEBop and METRIC). The reports on the first two phases of the study provide important background on ET and CU estimation methods in the basin (URS 2013; 2016). The overall recommendation from the reports is to support the ongoing shift to remote sensing-based methods with the installation of additional eddy covariance towers and enhanced weather stations that collect wind speed, humidity, and radiation, to improve validation and user confidence in the newer methods.

A multi-institutional effort is underway to create an open-source digital platform called [Open ET](#) to bring together different satellite observations and ET estimation methodologies to provide low cost, automated, and widely accessible ET data at multiple spatial and temporal scales.

Monitoring of evaporative demand

Evaporative demand is a measure of the “thirst” of the atmosphere or atmospheric dryness. It is quantified as the maximum rate of evapotranspiration for given atmospheric conditions and an unlimited supply of water; thus, it is effectively the same as reference ET (Hobbins and Huntington 2017). When sufficient moisture is available at the land surface, evaporative demand dictates the magnitude of ET fluxes. When evaporative demand is abnormally high for a period of weeks to months, particularly during the growing season, water use for irrigation and other sectors typically increases.

Open ET



Link:

<https://etdata.org/>

In situ

In situ measurement of evaporative demand is done through open-pan evaporation measurements. Real-time pan evaporation measurements are [available](#) from only a handful of stations within the Colorado River Basin, mainly in western Colorado, and therefore do not provide adequate spatial coverage of the region.

Modeled

Evaporative demand is usually computed using several different formulations that require meteorological inputs. The preferred formulation is Penman–Monteith, which is considered to be fully physical, incorporating temperature, humidity, wind speed and solar radiation, and is the same as reference ET. The Evaporative Demand Drought Index ([EDDI](#)) uses this formulation and the 12-km gridded meteorological input from NLDAS to quantify the relative evaporative demand over multiple user-defined timescales (weeks to months) for CONUS (Hobbins et al. 2016). EDDI data is updated daily, with a 5-day lag from real time.

CPC Evaporation Data

Link:
https://www.cpc.ncep.noaa.gov/products/GIS/GIS_DATA/JA_WF/

ESRL Evaporative Demand Drought Index

Link:
<https://www.esrl.noaa.gov/psd/eddi/>

5.6 Other remotely sensed hydrologic data relevant to the basin

Other remotely sensed hydrologic data types that do not fit neatly into the categories covered in previous sections of this chapter are summarized in Table 5.8, and discussed in the text below.

Table 5.8

Summary of other remotely sensed hydrologic data currently available (or to become available, in the case of SWOT). See the text for further description of these networks/products.

Mission or Product Name	Variables	Spatial Resolution	Spatial Coverage	Temporal Resolution
GRACE	Surface water + groundwater mass change	250–300 km	Global	Monthly
NDVI (MODIS, Landsat, VIIRS, Sentinel-2)	Vegetation greenness, differentiate between irrigated and non-irrigated lands	30 m–1 km	Global	Daily to monthly
EVI (MODIS, Landsat, VIIRS, Sentinel-2)	Vegetation growth and productivity	30 m–1 km	Global	Daily to monthly
NDWI (MODIS, Landsat, VIIRS, Sentinel-2)	Vegetation liquid water content	30 m–1 km	Global	Daily to monthly
SWOT (planned future mission)	River and lake water surface elevation	50 m	Global	Approximately monthly

Remote sensing of vegetation type/moisture content/irrigated area

There are several derived indices from satellite observations that provide monitoring of vegetation type and its moisture content, and differentiation between irrigated areas and non-irrigated ones. These indices include Normalized Difference Vegetation Index (NDVI), Enhanced Vegetation Index (EVI), and Normalized Difference Water Index (NDWI). Most of the basin states, as well as Reclamation, use satellite data to determine irrigated acreage and crop type.

NDVI measures vegetation greenness, and because it can capture the differences in the spectral responses between irrigated and non-irrigated croplands, it is highly applicable to mapping of irrigated areas (Ozdogan et al. 2010). However, NDVI is susceptible to atmospheric scattering and background canopy effects. EVI has been developed to address this issue. Relative to NDVI, EVI has an improved sensitivity to photosynthetic activity (i.e., vegetation growth and productivity) and does not have a saturation problem (Waring et al. 2006). Finally, NDWI has been developed to more robustly assess the liquid water content of the vegetation (Gao 1996). Near real-time information on these three indices are available from multiple satellites, including MODIS, Landsat, VIIRS, and Sentinel-2. Much of these data can be accessed from data portals such as Climate Engine.

GRACE: Terrestrial water storage change

The NASA Gravity Recovery and Climate Experiment (GRACE) mission, which consists of a twin satellite configuration, was launched in 2002. By detecting gravitational anomalies, GRACE provides precise monthly measurements of change in terrestrial mass, albeit at a very coarse (250–300 km) spatial resolution. Because these mass changes represent the change in combined surface water (including snow), soil moisture, and groundwater, the estimation of basin-scale total water storage over time is made feasible with GRACE data (Tapley et al. 2004). The partitioning of the different components of the water budget, however, requires land-surface modeling (Chapter 6).

Several studies have reported on different aspects of the GRACE-derived water budget for the Colorado River Basin. The first study highlighted the apparent magnitude of groundwater depletion in the Upper and Lower Basins from 2005–2014 (Castle et al. 2014), although Alley and Konikow (2015) asserted that that interpretation of the GRACE data was flawed. Scanlon et al. (2015) further showed that most of the downward trend in total water storage identified by Castle et al. (2014) was due to declines in soil moisture and reservoir storage.

More recent studies have compared the water budget for the basin derived from GRACE with water budgets from land-surface models and other

hydrology models, finding that GRACE shows larger annual fluxes of water than the models. These GRACE-model differences in the Colorado River Basin are not as large, however, as in many other basins around the world (Scanlon et al. 2018).

GRACE data has also been assimilated in NLDAS land surface modeling of groundwater, root-zone, and surface soil moisture at 1/8-degree (12-km) spatial resolution (GRACE-DA-DM; Kumar et al. 2016). Given the issues raised by Alley and Konikow (2015), assimilation of GRACE data in a land surface model may be a better approach for capturing its added value, versus direct interpretation of the GRACE data.

SWOT: Runoff and water elevation

Surface Water and Ocean Topography (SWOT) is a future (2021) NASA satellite mission that will provide information on water-surface elevations of lakes and large rivers with high accuracy (about 10cm) at monthly to seasonal scales. There are also plans to assimilate SWOT data into hydrological models to improve runoff information at very fine spatial scales.

5.7 Challenges and opportunities

Hydrologic data—whether for snowpack, streamflow, soil moisture, or evaporation—have enormous importance for all aspects of Colorado River Basin research, operations, and planning. Additional efforts to identify the challenges, improve and expand the historical record and current monitoring, and reduce uncertainties serve all interests. While pursuing new methods and data however, it is critical to maintain attention to the core monitoring capacity (SNOTEL network, stream gage network) that provides the foundation for those efforts and is chronically under-resourced.

In November 2019, USGS announced that the second Next-Generation Water Observing System (NGWOS) would be located in the Upper Basin, specifically the Colorado Headwaters above Cisco, UT, plus the Gunnison Basin. The objective of NGWOS is to intensively monitor up to ten medium-sized watersheds (10-20,000 sq. mi.) that are representative of larger regions. This advanced observing system will provide quantitative information on streamflow, ET, snowpack, soil moisture, a broad suite of water quality constituents, connections between groundwater and surface water, and water use. The new observations are intended to be used alongside those from existing monitoring networks in various operational and research applications, such as streamflow forecasting on multiple timescales. In the first year of the Colorado River NGWOS, the USGS will initiate planning and stakeholder engagement. This will be a valuable opportunity for stakeholders to shape and leverage a significant federal

effort to enhance the hydrologic observing capacity in key watersheds of the Upper Basin.

Challenges: Snow

- Inadequate characterization of the snowpack is still a major source of error in streamflow forecasts, especially in years with anomalous patterns of snow distribution in space and time—a phenomenon which appears to be more frequent in a changing climate.
- The in situ (point) snow course and SNOTEL network was designed for the statistical streamflow forecasting paradigm, which is no longer used by CBRFC.
- Many new spatially distributed SWE products are now available, but there have been few rigorous evaluations of these datasets, in part because it is difficult to validate spatial products with point measurements.
- The SNOTEL network will remain essential to any conceivable future snow monitoring system in the basin, especially with additional sensor capacity at SNOTEL sites, but the network has been inadequately supported in recent years by USDA.

Opportunities

- Building on recent smaller scale pilot efforts to conduct larger scale, systematic intercomparisons of SWE datasets and products for the basin, including SNOTEL, ASO, and SNODAS and other spatially distributed modeled products.
- Based on the results of such intercomparisons, pursuing “hybrid” approaches where multiple methods and datasets are combined in a way to best exploit their relative advantages.
- Continuing and stepping up the modernization and expansion of the SNOTEL network, with more and better sensors, more imagery, and better data communication—all of which would necessitate more resources for NRCS to support the network.

Challenges: Streamflow

- Streamflow observations that could contribute to more accurate naturalization calculations are not available at many key sites, especially diversion and return flow locations.
- Naturalizing the gage record requires adjustments that come with potential errors and uncertainties, many of which are impossible to address or resolve because of the dearth of early-period data and documentation.
- Fully characterizing the natural hydrology of the basin is problematic with the exclusion of the Gila River from consideration.
- A number of research activities use Reclamation’s natural flow record for baseline or reference purposes. For example, synthetic streamflow generation relies on the natural flow record for parameter estimation

or for nonparametric sampling (Chapter 9), tree-ring reconstructions of paleostreamflows (Chapter 10) are calibrated against the natural flows at Lees Ferry, and hydrologic simulations from the Variable Infiltration Capacity model that are used to project future streamflows were bias-corrected based on the natural flows at Lees Ferry and other gaging stations (Reclamation 2012c).

Opportunities

- Regarding gaging, the biggest gains in information going forward would be achieved by expanding the streamflow monitoring network to fill gaps in coverage. This includes gages at diversion sites and in locations to measure return flows or verify return flow and gain/loss calculations.
- Increasing the spatial resolution of Reclamation's models might be a useful avenue to pursue in order to simulate and analyze impacts from climate change on sub-basin hydrology.
- Major modifications to the natural flow record, to improve consumptive use estimates for example, have implications for both the calibrations and other applications listed above, and for the record extension back to 1906 because the extended records were based on statistical analyses of the natural flow record that was in place at the time of extension. As more recent natural flow data becomes available, there is an opportunity to revisit the characterizations, calibrations, bias-corrections, and record extension that were based on earlier versions of the natural flow record.

Challenges: Soil moisture and evaporation

- Compared with snowpack (which is variable over space and time), soil moisture is poorly monitored and understood, with frequent discrepancies between in situ measurements and modeled estimates.
- Real-time soil moisture data is collected from at least 6 different in situ networks, with differing observing protocols (depth, etc.).
- Reservoir evaporation estimates as used in basin system modeling have been based on decades-old data that does not reflect current climate conditions.
- Estimates of evapotranspiration and crop water use have been constrained by physically incomplete methods and input data that are not spatially representative.

Opportunities

- Support and expand ongoing efforts to comprehensively collate in situ soil moisture measurements and merge these observations with spatially distributed modeled estimates (e.g., National Soil Moisture Network).

- New satellite sensors and products (e.g., SMAP) that provide spatially comprehensive and consistent soil moisture estimates can likewise be compared and blended with other types of soil moisture data.
- When applicable, conduct testing of new soil moisture products to determine if they add value to the CBRFC forecast process.
- Ongoing efforts will provide updated reservoir evaporation estimates for Lakes Mead and Powell; those efforts could be expanded to other large reservoirs in the basin.
- Expand the in situ monitoring of evaporation/ET/PET with enhanced weather stations that capture all four variables needed for fully physical estimates (e.g. the Penman-Monteith method), and new flux towers needed for the Eddy Covariance method.
- Better in situ data will also help in calibrating/validating remote sensing-based spatial estimates of ET and crop water use; use of these spatial estimates in the basin has been increasing, though it has been limited by user confidence in the data.



Chapter 6

Hydrologic Models

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Key points

- With a range of hydrologic models readily available, it is important for prospective applications of models to articulate the objectives of the modeling as well as the requirements that the model must satisfy.
- A single model is likely designed for a specific application or context and may not be optimal for a wider range of uses.
- In the Colorado River Basin, the NWS models (streamflow forecasting) and the VIC model (sensitivity studies; climate change projection) have been the most-consulted hydrologic models for those respective applications. Each has varying capabilities and limitations.
- Increasing model complexity does not guarantee improved model performance. Complexity should be increased subject to the consideration of process needs, data sufficiency, computational feasibility, and ultimately the model's demonstrated performance.
- For some applications, such as streamflow forecasting at a river location, simpler models may continue to offer valuable and even superior performance for years to come.
- For other applications, such as understanding hydrologic sensitivity to climate change or hydrologic response to watershed changes, more complex process-oriented models are usually more appropriate.
- Calibration (parameter estimation) is almost always needed to achieve high-quality simulations in all hydrologic models, and it is easier to implement in simpler models than in computationally intensive complex models.

6.1 Overview

Hydrologic models are the foundation of broad range of applications in the Colorado River Basin, ranging from streamflow forecasting to trend analysis to climate change projection. This chapter provides an overview of hydrologic modeling, including perspectives on both model development and applications. There is some overlap with Chapter 8 (Streamflow Forecasting), but the additional applications of hydrologic models in basin water management and planning merits more thorough treatment of the models beyond their use in streamflow forecasting.

Hydrologic modeling refers to the use of simulations to characterize the likely behavior of real watershed features and systems (Allaby 2008). Hydrologic modeling can be applied to improve our understanding of hydrologic phenomena and how changes in, for example, pervious surfaces, vegetation, land use and weather and climate affect the hydrologic cycle. It is furthermore used to estimate runoff and water availability in the context of forecasts at timescales of hours to months, and projections over decades. The general components of a hydrologic model include

meteorological inputs (such as precipitation and temperature), governing equations enforcing physical laws (e.g., mass continuity), parameters, parameterizations (the algorithms specifying processes such as infiltration), and the model structure, including the arrangement and connectivity of watershed components (canopy, snowpack, subsurface) (e.g., Singh 1995; Clark et al. 2015).

The hydrologic models currently applied in the Colorado River Basin and elsewhere arise from several distinct traditions. The use of hydrologic models in streamflow forecasting (Chapter 8) has deep and practical roots in civil engineering, where models were developed to support water systems design and management (Anderson and Burt 1985). The communities driving these forecasting models tend to be operational agencies. In contrast, hydrologic models used in the projection of future hydrology to support water supply assessment (e.g., Chapter 11), or in trend and variability analysis, are mostly driven by academic institutions and agency research laboratories. These latter models have a stronger heritage in earth system modeling and watershed process modeling.

Despite their different origins, all models have watershed (or land) representations that involve terms for the common input and output fluxes and states, such as precipitation, temperature, soil moisture, snow water equivalent (SWE), runoff and evapotranspiration (ET). How these components are represented within the models, the way runoff is calculated, and the spatial interpretation of the model's catchment area can vary significantly from one model to another.

Model complexity and spatial framework

Hydrologic models can be viewed along a general continuum of complexity. Complexity can refer to the number of processes represented in the model, the spatial resolution of the model, or the structure and configuration of the model. With the rise of supercomputing as a resource for hydrology, the range of complexity for regional (e.g., Colorado River Basin) model applications has become ever broader. The lower bound of complexity has been set by the lumped conceptual configuration of traditional operational models, while the advancing upper bound tracks the evolution of very high resolution watershed process modeling approaches that were previously applied only in small scale studies.

This widening range of model complexity has prompted much debate in the research and operational communities (e.g., Grayson, Moore, and McMahon 1992a; 1992b; Reggiani, Sivapalan, and Hassanizadeh 1998; Beven 2002; Sivapalan et al. 2003; Maxwell and Miller 2005; Beven and Cloke 2012; Wood et al. 2012), with differing perspectives on issues such as the adequacy of representations of physical processes, and the impact of real-world data limitations and uncertainty. What is clear, though, is that there is no one

level of model complexity that is optimal for all applications. The following sections describe several general modeling approaches that differ in complexity, including the models used for the CBRFC's operational streamflow forecasting in the Colorado River Basin. (Streamflow forecasting itself is treated more thoroughly in Chapter 8.)

Conceptual and physical models

An initial distinction can be made between *conceptual* models and *physical* models—though models in each class may have elements of both, and these labels are inexact. Conceptual models have relatively simple representations of watershed attributes and processes, generally with no more than a dozen components. The relationships and linkages (fluxes of moisture or energy) between the components are typically controlled by adjustable parameters whose values may be only indirectly known from observations or otherwise deduced through calibration. The structure of the conceptual model is motivated by our understanding of the physics of the real world system (e.g., shallow and deep storage zones, percolation, radiation-driven snowmelt), but remains an extreme simplification of those physics. Conceptual models as well as physical models adhere to fundamental physical laws (such as mass and energy conservation) but conceptual models rely more much directly on external parameters to describe or specify hydrologic processes.

Physical models, also called process-based or mechanistic models, are generally more complex. They also contain many conceptual elements, but nonetheless represent the watershed attributes and processes with a higher degree of detail, and in arrangements that attempt to more closely mimic the storages of water and energy in the watershed and the fluxes between them. In contrast to conceptual models, physical models attempt to provide a more explicit representation of the hydrologic processes and the resulting hydrologic dynamics. Rather than allow an external parameter to directly control a process, they specify a physically informed equation describing the process (called a parameterization), which in turn is controlled by external parameters.

For example, in a conceptual model, the percolation rate from one storage zone to another may be determined by the storage amounts (states) and an external rate parameter specified in calibration. In contrast, the percolation in a physical model is determined by the storage states and an equation (and algorithm, a parameterization) that may calculate percolation also as a function of the soil properties assigned to the zones. These properties are often given by external parameters that may also be calibrated. As in conceptual models, the hydrologic responses in physical models are summations (i.e., an emergent behavior) of the hydrologic processes. Spatial and temporal variations in catchment characteristics are incorporated into physical models to a greater degree than conceptual

models, and consequently the structure and configuration of the physical models more closely reflect the real world watershed.

Notwithstanding the above discussion, it is important to note that a physical model is almost always applied at a scale larger than that at which some processes occur (see Clark et al. 2017 for a discussion). For example, a hydrologic model implemented at 12-km grid resolution is much coarser than the real world scale at which processes such as percolation of meltwater through a snowpack, or infiltration through soil, take place (which may be on a scale of centimeters). Thus, even though the description of a process may be through a physical parameterization, the model does not explicitly resolve that process, and remains, in a sense, also conceptual, and usually requires some degree of calibration.

Spatial framework

A second important distinction between models refers to the spatial framework of the model. Spatial variability in topography, geology, soils, and vegetation affects the hydrologic responses within a watershed (Clark et al. 2017). The spatial framework in hydrologic models can be categorized as lumped, semi-distributed, or fully distributed (Figure 6.1).

Lumped models average the spatial variability across a watershed unit; semi-distributed models reflect some spatial variability; and fully distributed models process spatial variability by many small spatial units

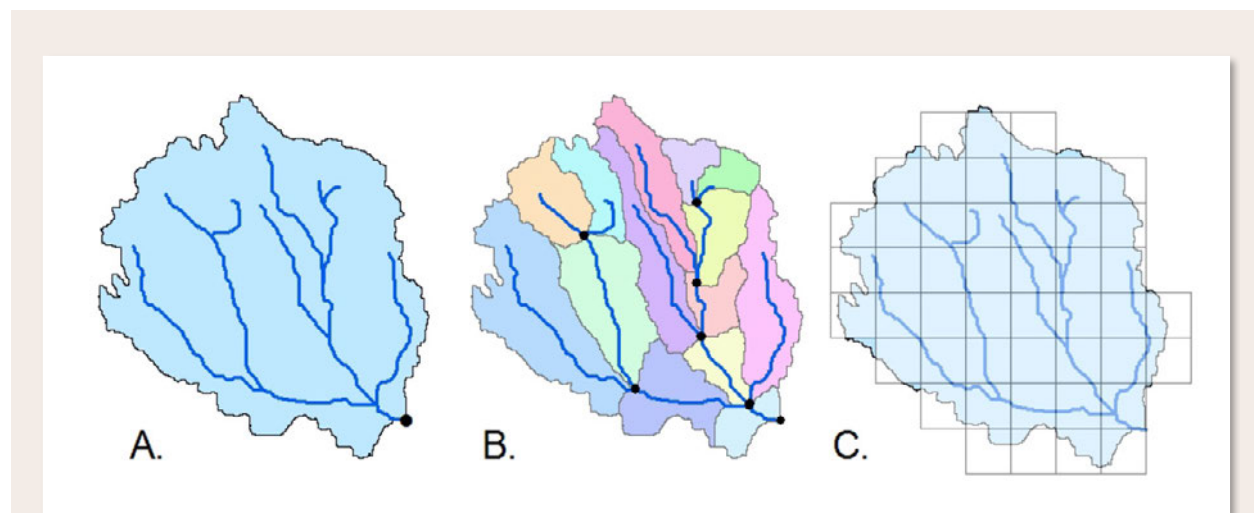


Figure 6.1

Schematic of the spatial frameworks in hydrologic models. **A:** Lumped model, **B:** Semi-distributed model by sub-catchment, **C:** Distributed model by grid cell. Runoff is calculated for each sub-catchment at the confluence points represented by the black dots in B. Distributed models calculate runoff for each grid cell, while lumped models calculate one runoff value for the entire catchment at the river outlet point represented by the black dot in A. (Source: Sitterson et al. 2017)

(usually grid cells). The spatial framework of each of the classes of models is given in Table 6.1. The spatial framework is strongly associated with the model class: conceptual models generally have a lumped framework, while physical models generally have a more distributed framework. It should be noted that terms such as “distributed” and “lumped” are labels reflecting model intent, rather than definitive descriptions of the characteristics of a model, especially resolution. For example, a 12-km distributed model may have similar spatial resolution and degree of spatial averaging as a lumped model broken into three elevation zones for the same watershed. Also, physical models may incorporate sub-grid variability for selected watershed attributes, such as vegetation and elevation.

Four general classes of hydrologic models

The characteristics of four general classes of hydrologic models are summarized in Table 6.1 and described in greater detail in the text that follows. Note that the distinctions among the model types are not hard and fast, and some models may blend aspects of two or more classes. Table 6.1 serves as an organizing reference for this chapter and is referred to throughout.

Table 6.1

Summary of characteristics of four general classes of hydrologic models. Terms are defined in the text.

	Bucket-style conceptual models	Stand-alone land surface models and multi-model frameworks	Land surface models in a coupled ESM system	Explicit watershed process models
Examples in the Colorado River Basin	Sac-SMA, SNOW-17, Monthly Water Balance Model	VIC, SUMMA	Community Land Model, Noah-MP, HTESSEL	WRF-Hydro terrain-routing, DHSVM, GSSHA
Model structure	Conceptual	A mixture of physically explicit and conceptual components	A mixture of physically explicit and conceptual components	Physical, with fewer unresolved (conceptual) process components
Spatial framework	Lumped or semi-distributed	Distributed, but can have lumped components	Distributed	Distributed
Typical Resolution	3–30 km, or 10–1000 km ² hydrologic unit	500 m–25 km	10–100 km	10–500 m

	Bucket-style conceptual models	Stand-alone land surface models and multi-model frameworks	Land surface models in a coupled ESM system	Explicit watershed process models
Primary applications in the Colorado River Basin	Operational streamflow forecasting, sensitivity analyses, coarse-scale climate-change impact analysis	Climate sensitivity analyses, climate change and variability impacts, streamflow forecasting	Weather and climate prediction, variability analysis, and climate projection	Hydrologic process studies (e.g., surface-groundwater interactions, ET modeling, snow hydrology), climate variability and change studies
Advantages	Computationally cheap, highly amenable to calibration (parameter estimation), agile for running ensembles and data assimilation, typically the highest-performing model for streamflow simulation and forecasting (within the calibration envelope)	Computationally feasible for most applications but requires high-performance computing for large domains, more process-oriented, maintains water and energy balance, more trusted for analysis beyond the calibration envelope, designed for regional to global implementation	Includes land-atmosphere feedbacks and a greater variety of process representations (including carbon cycle and dynamic vegetation in some cases), albeit at a coarser scale due to coupling in continental and global scale applications	Can represent hydrologic processes with more explicit detail and granularity, suitable for evaluation of high-resolution observations, can better represent explicit terrain and vegetation influence on hydrologic phenomena
Disadvantages	Conceptual representation and simplification of physical processes and extensive calibration limit the ability to simulate multiple outputs and project significantly beyond the calibration envelope	Computationally demanding relative to conceptual schemes, and structure, parameterization inflexibility can undermine performance and hamper calibration	Application in the coupled context in which atmospheric variables are often most important means that hydrologic quantities such as runoff or snowpack are less scrutinized and less calibrated	Computational demands restrict or degrade many applications, including long-range or large-domain simulation, comprehensive parameter estimation, and use of ensemble techniques

Bucket-style conceptual models

Conceptual models can be viewed as being based on the assumption that we know (or once *knew*) relatively little about the real world structure and functioning of a watershed, therefore we use a minimal structure, and infer parameters to directly control processes from observations. This strategy has been shown to work well where there are sufficient data for calibration and inputs, despite concerns about the extent to which the resulting parameters are overly tuned to the data.

At the time these models were initially developed in the 1960s and 1970s, the main motivation for the relatively simple representation of a watershed was to make the model supportable by the limited available weather and hydrology data at that time, which were almost entirely point-based (Chapters 4 & 5). But even today, these simple hydrologic models produce highly accurate simulations and forecasts that are difficult to outperform using physical models.

Bucket style conceptual models remain relatively simple, with lumped modeling units of small watershed areas, on the order of 10–1000 km². This lower complexity, with consequently lower computational demands, is

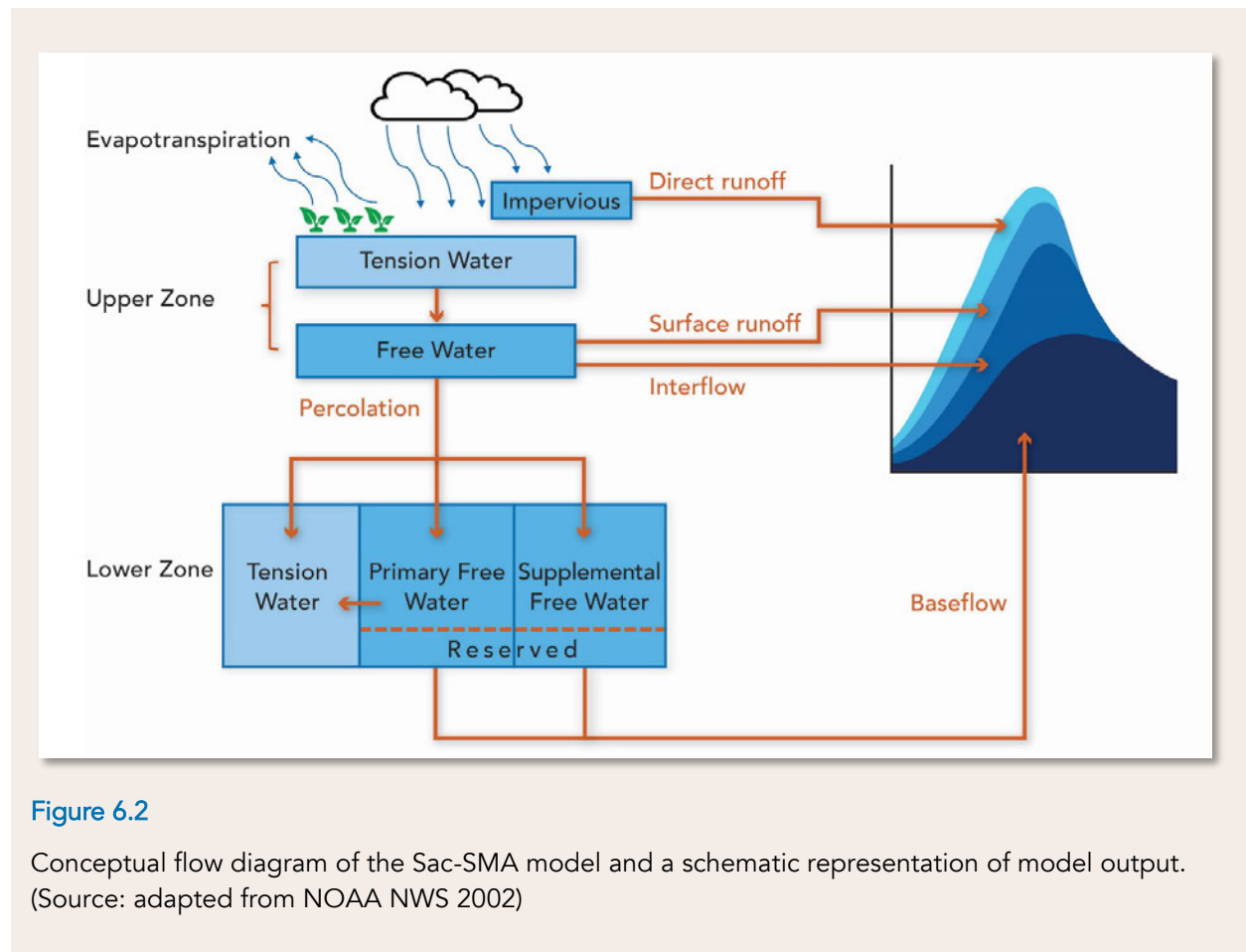


Figure 6.2

Conceptual flow diagram of the Sac-SMA model and a schematic representation of model output. (Source: adapted from NOAA NWS 2002)

advantageous because it enables manual calibration in the model development phase, and facilitates forecasters' examining and iteratively updating their inputs, states, and outputs in real-time during the forecasting workflow. An example of a traditional lumped approach is provided in Figure 6.2.

The conceptual hydrology model whose output is most familiar to Colorado River stakeholders is the Sacramento Soil Moisture Accounting Model (Sac-SMA) used by the CBRFC and other National Weather Service (NWS) River Forecast Centers (RFCs) for operational streamflow forecasting (Figure 6.2). Sac-SMA has five soil storage types ("buckets"), each with an underlying physical rationale. For example, the upper zone tension water content bucket represents the portion of the soil column that experiences unsaturated flow and in which capillary pressure in soil pores resists drainage and lateral flow. Figure 6.3 shows an example of the output of Sac-

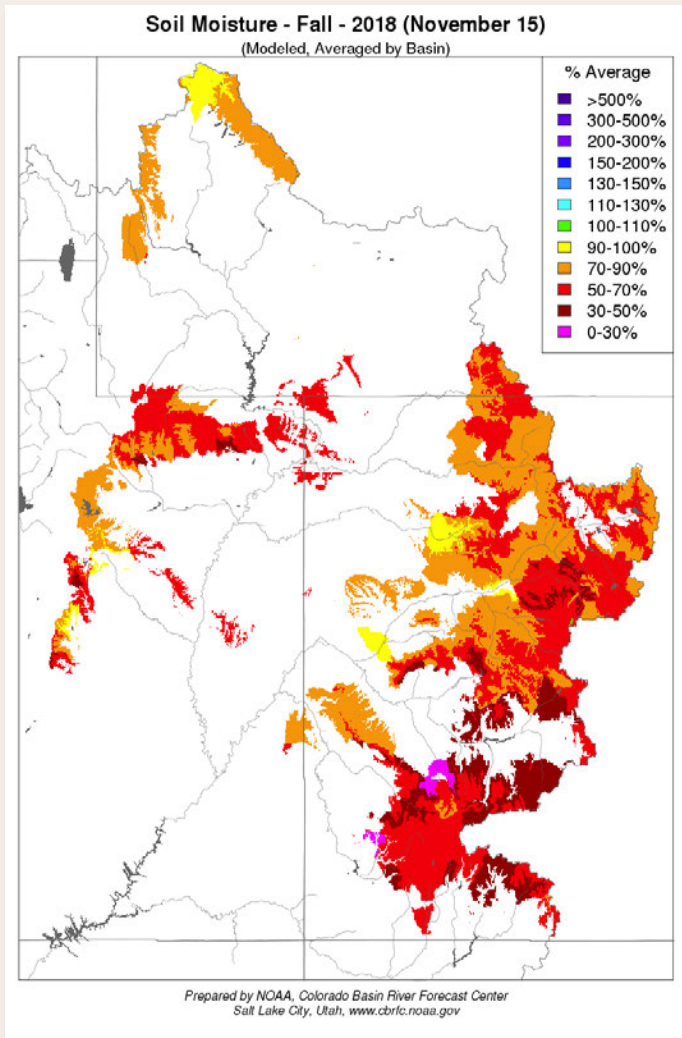


Figure 6.3

Example of model output of Sac-SMA for the upper Colorado River Basin. Note the lumped nature of the model output. (Source: NOAA NWS CBRFC; https://www.cbrfc.noaa.gov/wsupsac_sm/sac_sm.php)

SMA, which is operationally paired with SNOW-17 (Anderson 1973), a temperature-index based conceptual snow accumulation and ablation model. See section 6.3 for a more detailed description of the NWS models.

Stand-alone land surface models (LSMs)

Stand-alone land surface models (LSMs) such as the Variable Infiltration Capacity (VIC) model are physical models and differ from conceptual

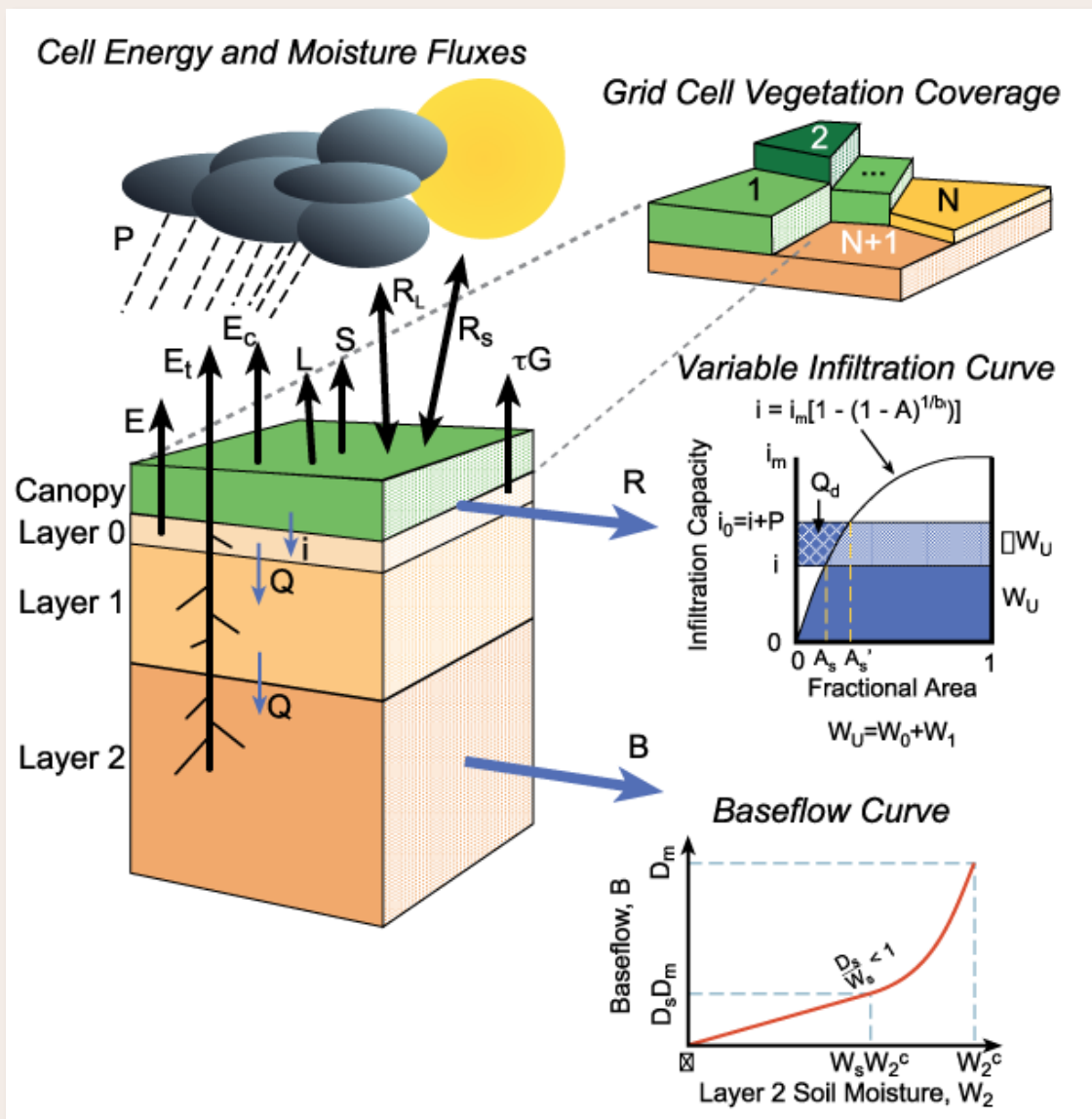


Figure 6.4

Schematic representation of the VIC model, showing land cover tiles, soil column, and major water and energy fluxes (Source: VIC Model Overview, <https://vic.readthedocs.io/en/master/Overview/ModelOverview/>)

models in that the states, inputs, and outputs are designed to emulate physical processes more explicitly (Figure 6.4).

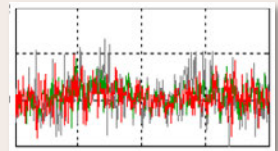
LSMs use physical equations and other quantitative methods to simulate the exchange of water and energy fluxes at the Earth surface–atmosphere interface. For example, LSMs dynamically calculate potential ET (PET) and simulate evaporative fluxes through parametrizations of sub-processes such as vegetation transpiration and bare soil evaporation, while conceptual models may lack a representation of vegetation entirely, or take PET as an input or use PET as a parameter that is tuned in calibration.

Since their advent in the 1990s, VIC and similar land surface models have demonstrated their utility for a broader range of hydrologic analyses, including the assessment of long-term trends in regional hydrology (Mote et al. 2005), drought (Andreadis et al. 2005), streamflow forecasting (Hamlet and Lettenmaier 1999; Wood et al. 2002), climate change detection and attribution studies (e.g., Barnett et al. 2008) and impact assessment. In the Colorado River Basin alone, as discussed in Chapter 11, VIC has been used for at least a half dozen studies and is the basis for the major climate change hydrology datasets developed by a Reclamation-led consortium and archived at the Lawrence Livermore National Laboratory [website](#). See section 6.3 for a more detailed description of the VIC model.

As alluded to earlier, VIC has parameters directly regulating the subsurface stores of water and the transfer (fluxes) of water from one storage layer to another. For soil drainage, where a conceptual model might apply a linear reservoir formulation in which the outflow from one bucket to the next is linearly related to the bucket's current water storage, a land surface model such as VIC represents water storage and transfer in terms of process concepts and attempts to specify parameters using observed, or estimated, geophysical attributes.

In a land surface model, soil drainage in the saturated zone may be described by a Darcy's law representation in which drainage rate is dependent on the amount of water in the column and a hydraulic conductivity parameter that is estimated based on the soil texture. However, because soil textures are very sparsely observed, the relationship between soil textures and the conductivity parameter are uncertain, and soil drainage is simulated at a spatial scale (e.g., 12 km) that is much larger than the scale at which the drainage process acts, this physically based model parameterization may be almost as rough an approximation of the real-world process as found in the conceptual model formulation. The hydraulic conductivity, soil layer depths and other physical parameters may also be used as calibration parameters, meaning that the soil drainage process in a physically based land surface model application may effectively be as "tuned" as the water transfer in a conceptual model. The greater

Downscaled CMIP3 and CMIP5 Climate and Hydrology Projections



Link:
https://gdo-dcp.ucllnl.org/downscaled_cmip_projections/dcplnterface.html

process realism in the land surface model (or any physical model) and its distributed nature requires a far larger number of sensitive parameters—many of which may be hidden in the code through hardwiring (Mendoza et al. 2015)—and more complex model structure. The result can often be a model that is less amenable to calibration, that is, less flexible for tuning to reproduce observed variability for an output such as streamflow.

Table 6.1 provides a summary of the advantages, disadvantages and applications of stand-alone LSMs used in the Colorado River Basin. Figure 6.5 shows an example of VIC model output.

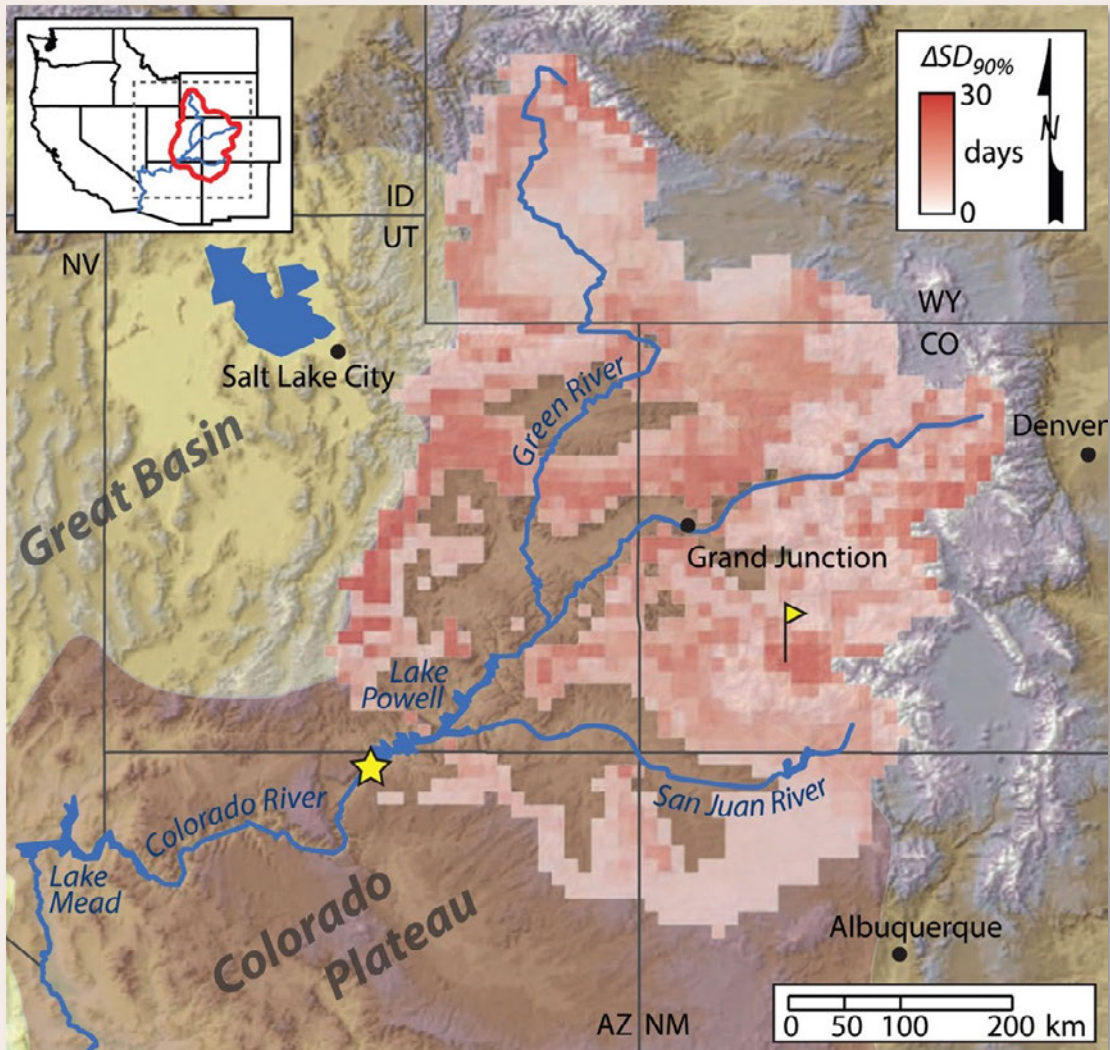


Figure 6.5

Example of output from an application of the VIC model in the Colorado River Basin. The red shading shows the mean difference per cell in the timing of snow depletion ($\Delta SD_{90\%}$, i.e., the change in the date at which 10% of the peak snowpack remains) between 'Before Dust Loading' and 'After Dust Loading' scenarios for 1916–2003. (Source: Painter et al. 2010)

Land surface models (LSMs) in a coupled system

Over the last few decades, the land surface has become an increasingly well represented component in climate models. A GCM (from “General Circulation Model” or “Global Climate Model”) is a modeling framework that couples a global atmospheric model, an ocean model, a sea ice model, and a land surface model (see Chapter 11). An Earth System Model (ESM) extends a GCM to include a suite of more detailed sub-models, including representations of the biogeochemistry of the ocean and land (e.g., carbon cycle, nutrient cycle, etc.), atmospheric chemistry, dynamic ice sheets (Lenaerts et al. 2019), dynamic vegetation, and water management.

Recently, computing capabilities have advanced such that more complex land surface schemes are being included in coupled GCMs and ESMs. Land surface models such as the NCAR Community Land Model (CLM) now incorporate detailed physics to represent land surface moisture and energy fluxes (e.g., the impacts of surface albedo on longwave and shortwave radiation), including the influence of land cover changes and idealized hillslope-scale effects on moisture distribution (Figure 6.6). Although these models are still run at a relatively coarse resolution (e.g., >25 km), some have more detailed parameterizations than a typical hydrology model like VIC, and far more detailed process descriptions than are found in conceptual models. This additional detail allows representation of processes such as vegetation dynamics and carbon-cycle physics that are key feedbacks into the climate system.

A long-sought objective for hydrologic science is to bring about a convergence in modeling so that local scale hydrology can be simulated by GCMs and ESMs, negating the need for calibrated stand-alone hydrology models like VIC (Fan et al. 2019). Lehner et al. (2019) provide a detailed perspective on the limitations of current (CMIP5) land surface models within GCMs to simulate runoff and runoff sensitivities in the Upper Basin (see Chapter 11). NCAR is currently developing a potential successor to the Community Land Model called the Community Terrestrial Systems Model (CTSM) that will ultimately be a more complete land model, including anthropogenic impairments (i.e., water management and irrigation at a coarse scale), and may soon have test case implementations that are usable for hydrologic applications related to water management.

The Weather Research and Forecasting Hydrologic modeling system (WRF-Hydro) used by the National Water Model (NWM; see section 6.3) is an outgrowth of both process-oriented watershed modeling and developments in the field of earth system modeling. In principle, WRF-Hydro can couple a land-surface model (primarily Noah-MP), a weather research and forecast model (WRF), a terrain routing model, a groundwater bucket model, and channel routing. However, WRF-Hydro in the NWM implementation is not actually coupled with WRF.

The last decade has also seen the rise of operational global domain models that are used for hydrologic analysis and prediction. Two operational forecasting centers, the European Centre for Medium-Range Weather Forecasts (ECMWF) and the Swedish Meteorological and Hydrologic Institute (SMHI), are now producing naturalized seasonal hydrologic runoff forecasts for continental to global domains (Wetterhall and Di Giuseppe 2018; Emerton et al. 2018). Deltares, a research institute in the Netherlands, also runs a global, grid-based model for medium range ensemble forecasting in a system called the Global Flood Forecast Information System (GLOFFIS). It is now straightforward for large-scale modeling centers to link land surface and routing models to provide up-to-global scale hydrologic simulations. For instance, NCAR recently linked CLM runoff output with the MizuRoute channel routing model (Mizukami et al. 2016) to simulate streamflow for all of North America (Figure 6.7). NASA and other agency partners run the Famine Early Warning System (FEWS), which is based on global LSM applications, and universities such as Princeton and the University of Washington have run various LSM-based forecasting systems (e.g., with VIC) for over 15 years.

These continental to global efforts are all still in the initial stages. Their skill remains relatively unexplored and is often quite poor, yet it is worth noting them as a possible harbinger of future information resources and development. It is also possible that their forecasted natural runoff anomalies (e.g., percent of average) may be informative; they are driven by good quality weather and climate forecasts and could in some cases provide useful information in spite of model bias. The poor forecast quality is likely to improve in the future given that these modeling efforts are often tied to sizeable research and development resources and bring to bear high quality datasets and techniques that may not have been adopted in local scale forecasting. Many of them also are linked to long, consistent hindcasts that enable users to gage their skill and even bias-correct them, something that is unavailable in NWS real-time streamflow forecasts. Their current potential is likely to lie more in medium-range and seasonal (mid-range) forecasting, with short-range predictions from tailored, more local systems being relatively more actionable.

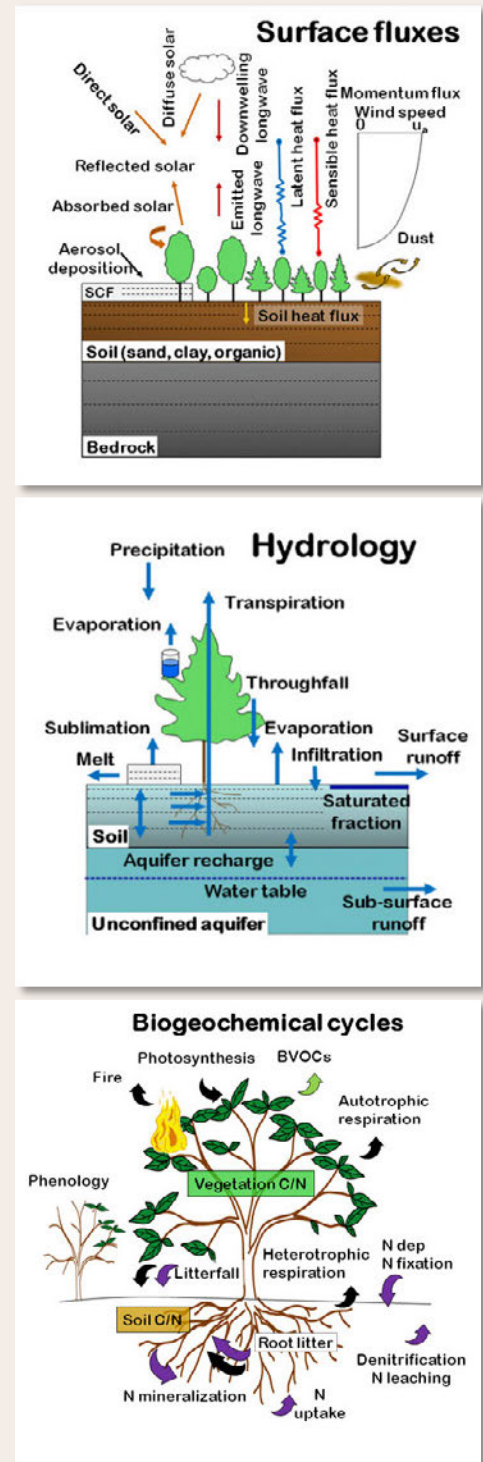


Figure 6.6 Schematic of the structural and physical characteristics of the Community Land Model (Source: "Community Land Model" <http://www.cesm.ucar.edu/models/clm/>)

Explicit watershed process models

Models applied within the discipline of fine-scale watershed science, which are often linked with intensively instrumented watershed observing networks, attempt to resolve watershed and hillslope-scale processes—interception, throughfall, myriad snow processes, infiltration, and vertical and lateral flow in saturated and unsaturated soils—in as much explicit detail as possible. Examples of such models include Gridded Surface/Subsurface Hydrologic Analysis (GSSHA), the Distributed Hydrology Soil Vegetation Model (DHSVM) (Figure 6.8), and the terrain-routing model included in the WRF-Hydro system.

A defining feature of the explicit watershed process model is the use of terrain gradients to drive lateral fluxes of water both overland and through the soil column, so that the runoff generation mechanism accounts not just for vertical fluxes of moisture but also the role of the landscape in distributing moisture horizontally, which is not represented in other types of models. In such models, groundwater can emerge at the surface at a break in grade, can flow downhill overland or within a fine-scale channel network, and then re-infiltrate the soil. In contrast, land surface models such as the VIC model, have simpler runoff-generation mechanisms, motivated by the assumption that the lateral fluxes of water between grid cells are much smaller than transport in channels (e.g., streamflow) and the vertical fluxes of ET and drainage. Table 6.1 provides a summary of the advantages, disadvantages and applications of explicit watershed process models used in the Colorado River Basin. Figure 6.9 shows an example of DHSVM model output.

Some watershed process models have distributed snow algorithms that allow for blowing and drifting effects caused by terrain and forcing variations. Because the models resolve vegetation almost down to the scale of an individual tree (about 10 m), or at least at the scale of a forest stand (about 100 m), the role of local vegetation in the hydrologic cycle is often explicitly represented, and described by many parameters. In fact, the development of DHSVM was motivated by an interest in quantifying forest harvest effects on runoff, including the impacts of individual roads and culverts.

The scale of such models is still far coarser than the scale at which processes such as soil infiltration occur (Clark et al. 2017; Seyfried and Wilcox 1995), thus like land surface models they are in some measure a conceptual representation, but their process orientation is still clearly greater than land surface models.

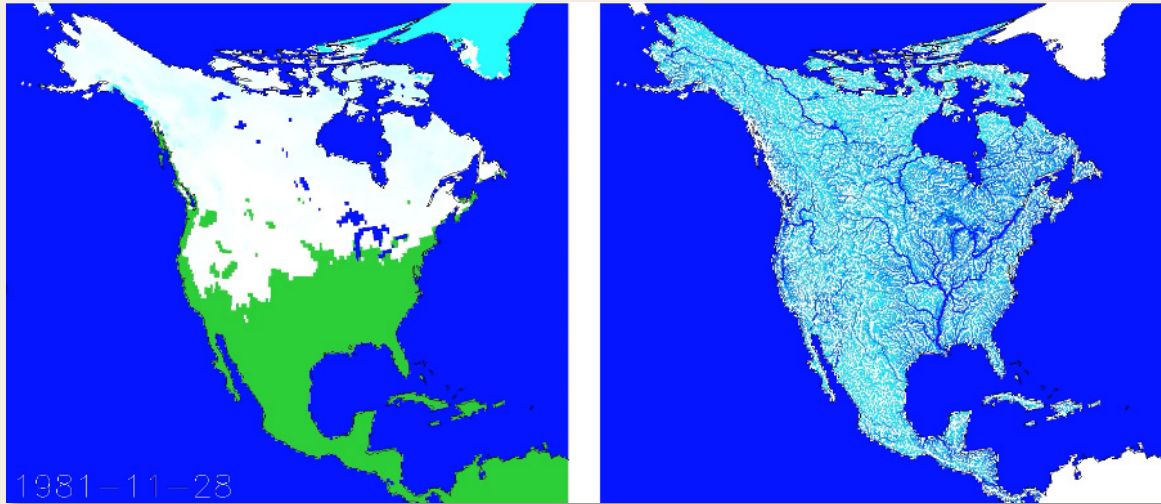


Figure 6.7

The convergence of continental-scale land surface modeling with streamflow simulation at watershed scales is illustrated by the coupling of a gridded CLM-based land model, illustrated by its SWE output (left), to a reach-based channel routing model (Mizuroute) implemented across North America to obtain streamflow (right). (Source: N. Mizukami and M. Clark, <http://www.cesm.ucar.edu/events/wg-meetings/2019/lmbwg.html>)

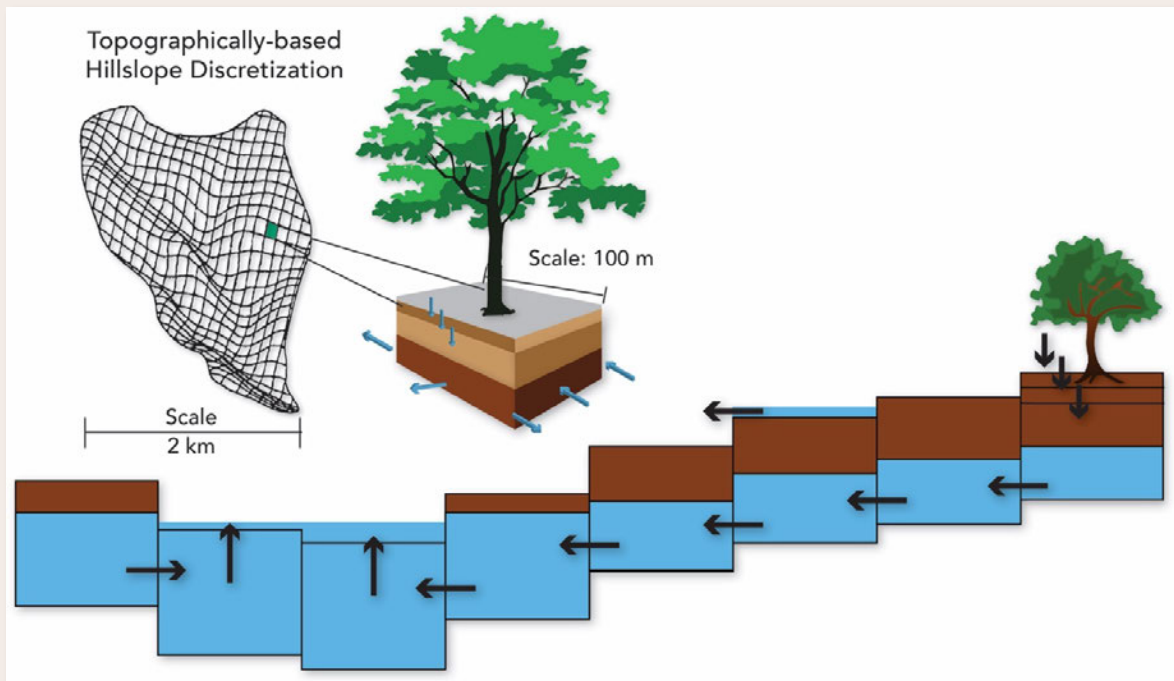


Figure 6.8

DHSVM model representation. (Source: adapted from Wigmosta, Vail, and Lettenmaier 1994)

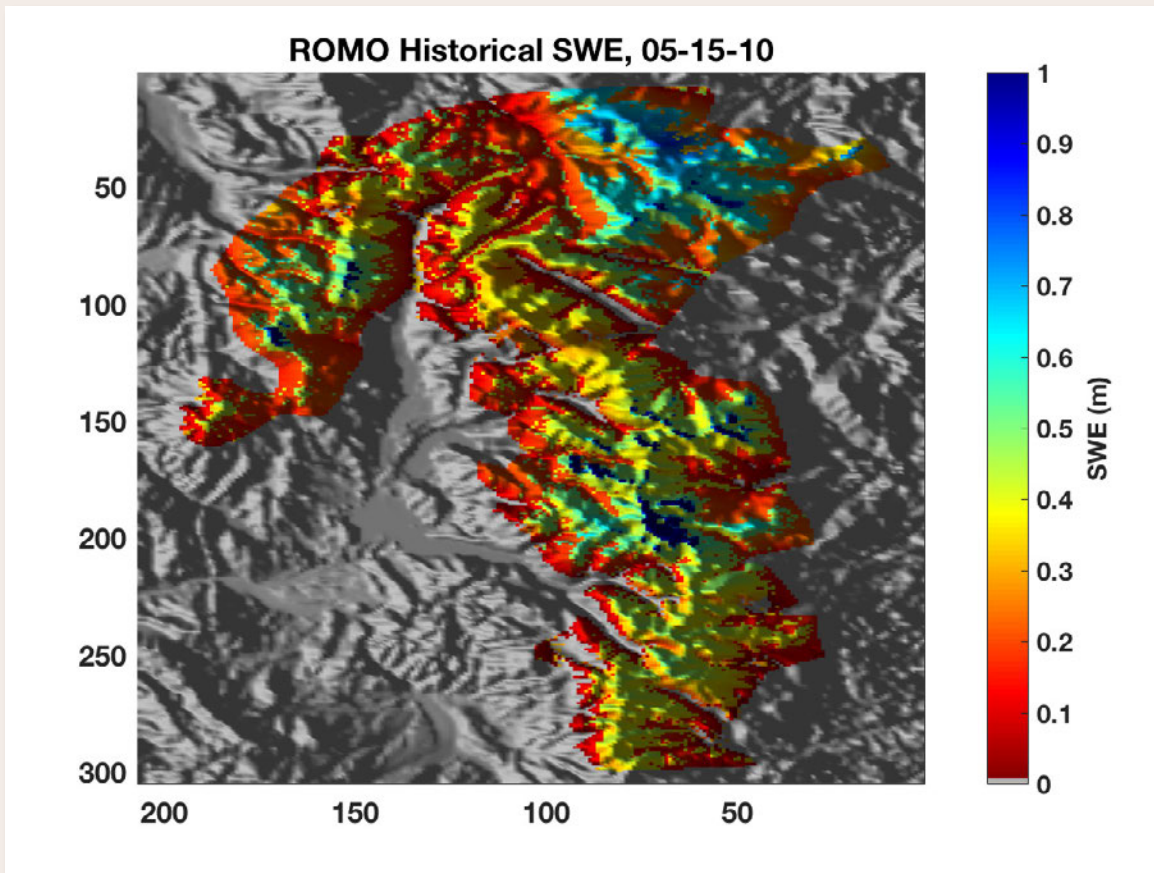


Figure 6.9

Example model output of DHSVM, showing simulated SWE for May 15th at a 250-m resolution, given observed historical temperature and precipitation data. The modeled area includes drainages in and near Rocky Mountain National Park. (Source: Aaron Heldmyer, CIRES)

Most applications of high-resolution explicit process models have been to support the investigation of geophysical questions in watershed science and ecology, including understanding the effects of beetle kill, juniper control strategies, forest thinning approaches, dust-on-snow phenomena, deglaciation, and groundwater-surface water interactions, among other topics. Until recently, it had been rare to find such models used in water resources applications such as streamflow forecasting or long-term climate change studies. In the U.S., Westrick, Storck, and Mass (2002) implemented a 150-m DHSVM model for streamflow prediction in the Pacific Northwest. More recently and notably, NOAA NWS launched the NWM for streamflow forecasting which coupled a 1-km resolution implementation of the Noah-Multiparameterization Land Surface Model (Noah-MP; Niu et al. 2011) to a 250-m terrain routing scheme (Gochis, Yu, and Yates 2015). See section 6.3 for a more detailed description of the NWM.

The use of such computationally intensive models for real-time forecasting as well as for geophysical process studies is enabled through advances in high-to-hyper resolution imagery, inexpensive supercomputing, broadband connectivity, and petabyte-scale data storage. Nonetheless, this technological progress is not quite adequate to make high-resolution (10–500 m) process-oriented models attractive (or feasible) for large-scale regional applications and long-range predictions or projections. The need to estimate model parameters at such fine scales and over large domains remains a scientific challenge that is not alleviated by more explicit spatial resolution or more complex physical parametrizations. While some hydrometeorological dynamics can be better captured by such schemes (such as terrain impacts on snow deposition), the need to calibrate many other parameters in a more unwieldy model is a major obstacle to achieving improved simulations.

New and emerging modeling approaches

In addition to the aforementioned hydrologic model types already used in the Colorado River Basin, there are several new modeling efforts underway that are still in early stages of development. These efforts focus on providing streamflow simulations. One is an application of the current NWM long-range configuration on a HUC12 catchment basis, which could offer a less computationally intensive and more calibratable model for mid-range (seasonal) Ensemble Streamflow Prediction (ESP). Another is the application of the Structure for Unifying Multiple Modeling Alternatives (SUMMA; Clark et al. 2015a, 2015b), also on a watershed HUC12 basis, for the entire U.S. as well as the Reclamation western U.S. management domain. A third is a research effort to integrate an energy balance snow model into RFC operational use, coupled with an 800-m Hydrologic Laboratory-Research Distributed Hydrologic Model (HL-RDHM) implementation. This effort was a NASA-funded collaboration between the CBRFC, Utah State University, and Riverside Technologies, Inc. (RTI, Fort Collins).

A very rapidly emerging modeling approach is the use of machine learning methods (e.g., neural networks) to produce watershed model simulations trained only on observed datasets, without any explicit representation of physical processes within the model. Since the machine learning modeling approach has been primarily applied to forecasting, it is discussed in more detail in Chapter 8.

Selecting appropriate models for different applications

As is shown in Table 6.1, different model classes and individual models have different characteristics and inherent advantages and disadvantages. Therefore, it is important to carefully articulate the modeling objectives, as well as the requirements a model must satisfy, prior to selecting a certain type of model. The limitations of data availability, time, and budget need to be identified to narrow the choices and select the appropriate model for

the intended purpose (Sitterson et al. 2017). In practice, the need to identify all these different aspects is rarely met or even recognized. More often, a model is chosen for an attribute that may appear desirable for one objective, but greatly limits its potential to satisfy another objective. For example, the desire to implement, in the NWM, a model with a “street-scale” resolution led to an implementation that is not well suited for seasonal forecasting. In the case of the monthly calibrated VIC model, a desire to understand and project climate sensitivities is pushing increasingly beyond the capacity of the VIC physics to provide the required physical fidelity.

Despite recent interest in the idea of a “seamless” modeling approach that can, in principle, satisfy every use case, it is unclear that this is possible or desirable as a strategy for achieving multiple objectives optimally, let alone all possible objectives of interest to a water manager.

6.2 Model applications in the Colorado River Basin

Forecasting

The most well-known hydrologic modeling activities in the Colorado River Basin, and the most critical to water management, are the use of NWS models (e.g., Sac-SMA) within the Community Hydrologic Prediction System (CHPS) operational platform. They are used to produce real-time, single-value flood forecasts (out to 10 days lead time in most cases) and seasonal (mid-range) ensemble forecasts via ESP techniques (explained in Chapter 8). In addition, the NWS HL-RHDM is now being used by the CBRFC in an effort to experiment with distributed modeling and snow data assimilation for forecasting in the Upper Basin.

Although not originally designed for forecasting purposes, the VIC model has also been used in a number of research and quasi-operational forecast studies in the Colorado River Basin, run at $1/8^{\text{th}}$ degree (12 km) and used to simulate streamflows at daily time steps at several dozen locations with medium-sized to large drainages (3,000–500,000 km²) upstream. The focus of the VIC-based forecast effort has always been on seasonal streamflows and addressing questions about the potential value of seasonal climate forecast information (Wood, Kumar, and Lettenmaier 2005). Models arising from research efforts at the University of Washington in the 2000s were typically calibrated, using either manual or automated objective methods, to the naturalized streamflow dataset from Reclamation, much of which is at a monthly time step (Chapter 5). More recently, researchers at Los Alamos National Lab have recalibrated VIC at $1/16^{\text{th}}$ degree (6 km), but that model has not yet been applied to forecasting.

Climate change impact projection and assessment

In the key locations used by Reclamation for management of the Colorado River Basin—i.e., larger headwater and tributary basins and mainstem locations—and at monthly scales, VIC's performance has been adequate to support long-range climate change impact assessments as well as mid-range ensemble streamflow prediction. The 1/8th degree VIC's greater process orientation (compared to the NWS models) has made it more acceptable for climate change studies, but there are also many ways in which VIC's physics are limited, and may not capture important dynamics that could alter projected hydrologic outcomes. These include surface water-groundwater interactions, dust-on-snow effects, dynamic vegetation influences, sub-grid variability in meteorological variables, and near-surface land-atmosphere feedbacks. Among the land surface models, VIC has dominated the usage for climate change impact assessment, becoming a *de facto* standard for the basin (see Table 11.4).

The NWS models have also been used for climate change impact assessment in the basin (e.g., Miller et al. 2011; 2012; 2013; Woodbury et al. 2012; Bardsley et al. 2013). However, because they lack an explicit energy balance, the NWS models are not as inherently suited as VIC for simulation of conditions beyond the envelope of weather and climate to which the models have been exposed in calibration and operational use. For example, for the studies cited above, the fixed monthly cycle of potential evapotranspiration (PET) had to be replaced with a dynamic PET representation based only on temperature change, lacking the other factors that influence PET such as solar radiation, humidity, and wind.

Some climate change studies extend beyond the quantification of climate change impacts to focus also on the statistical detection of hydrologic impacts and attribution to anthropogenically forced climate change. The VIC model has been applied to such detection and attribution studies, including for the western U.S. and the Colorado River Basin (e.g., Barnett et al. 2008; Pierce et al. 2008). The VIC model developed for the Colorado River Basin and run at 1/8th degree has also provided good research-quality naturalized flow simulations in various implementations for many analyses and studies over the past 15 years. Calibration to monthly naturalized flows has meant that their daily flow simulation, and simulation for basins for which they were not directly calibrated, is less optimized and substantially poorer than what is provided by NWS models like those used by the CBRFC. A gradual evolution of the VIC code, without accompanying recalibration, has also led to a degradation in model simulation quality.

Sensitivity studies

An increasingly active model application in the Colorado River Basin is sensitivity analysis—introduced in Chapter 2—which involves exploring observed trends and variability in basin hydrology and attempting to

quantify their sensitivity to temperature, precipitation, and other climate factors. Sensitivity studies are important because they can provide a shorthand strategy for gauging the potential impacts of climate change on a basin's hydrology, and consequently water resources. Sensitivity analyses have been based on observations from the historical record as well as on paleo datasets, and on hydrologic models.

While observations are seen as reliable because their measurement accuracy and uncertainties are relatively well understood, models are attractive because they enable a controlled testing of the sensitivities of natural processes such as runoff generation through strategies like perturbing input meteorology; e.g., assessing the impact of a 10% decline in precipitation. The major drawback of models in this context is that they rely on the assumption that the model faithfully represents key watershed processes and their linkages to the independent variables of interest. While an integrated model output variable such as streamflow can be easily validated against observations, and errors in inputs may be indirectly estimated, it is rare that the sensitivities of intermediate sub-processes, such as infiltration or sublimation, and their completeness (e.g., whether all controlling processes are incorporated in the model) are evaluated and confirmed as being realistic. Consequently, model-based sensitivity analyses are inevitably dependent on the partially assessed fidelity of the model. Currently, the CBRFC is working on an accuracy assessment and sensitivity analysis of hydroclimatic parameters within the CBRFC modeling framework. The goal of this work is to improve the accuracy of the CBRFC's water supply forecast.

The primary models that have been used in sensitivity studies for the basin are all LSMs, with the VIC model being the most frequently used (Vano, Das, and Lettenmaier 2012; Vano and Lettenmaier 2014; Vano et al. 2014; Xiao, Udall, and Lettenmaier 2018). Among these sensitivity studies, Vano, Das, and Lettenmaier (2012) and Vano et al. (2014) also examined the output of other LSMs—CLM, Catchment, and Noah—as well as Sac-SMA. The latter of these two studies also looked at another conceptual model, the Simple Water-Balance Model presented by McCabe and Markstrom (2007), which had previously been used to model Colorado River Basin water supply risk (McCabe and Wolock 2007). As the name suggests, this model has a much simpler formulation of watershed processes compared to the other models discussed in this chapter. For example, the occurrence of snow is determined by precipitation falling below a mean monthly temperature threshold, which is a calibrated parameter. The model's ET is dependent on water availability and driven by Thornthwaite estimates of PET, which are sensitive to temperature but not radiation. It should be noted that the monthly time step of this model increases uncertainties considerably due to averaging of inputs and outputs that are often nonlinear.

6.3 Descriptions of key hydrologic models relevant to the basin

In the Colorado River Basin, the most frequently consulted hydrologic models have been the NWS models (Sac-SMA and SNOW-17) for streamflow forecasting, and the VIC model for sensitivity studies and climate-change projections of hydrology. These models also exemplify their respective broader classes of models (conceptual models and land surface models) as summarized in Section 6.1. Below are extended descriptions of these two models, their setup and use, and calibration and inputs. The National Water Model (i.e., WRF-Hydro and other components) is also described, even though it is not (yet) in operational use in the basin, because it represents recent trends and new methods in hydrologic modeling, and because NOAA intends for it to become the operational model for the NWS RFCs, including the CBRFC, in the future.

National Weather Service models

In the 1970s, the National Weather Service began developing the River Forecast System (NWSRFS), a collection of interrelated software and data capable of performing a wide variety of hydrologic and hydraulic functions. The primary hydrology model deployed within NWSRFS was actually two models: Sac-SMA for modeling precipitation-runoff processes, and SNOW-17 for modeling snow accumulation and ablation. Other models developed for use within NWSRFS accounted for agricultural water use, conversion of runoff volume into instantaneous discharge (i.e., unit hydrograph implementation), reservoir operations, and other hydrologic processes. In 2012, most of the legacy hydrologic models and other software of NWSRFS, including Sac-SMA and SNOW-17, were migrated into a new software platform, the Community Hydrologic Prediction System (CHPS).

CHPS is an interactive platform that specifies models and operations within a workflow to run both short-range streamflow and flood forecasts and seasonal (mid-range) ensemble streamflow prediction (ESP) forecasts. CHPS is the NWS implementation of the Delft-FEWS software platform. Since its deployment at the CBRFC and the other RFCs beginning in the early 2010s, CHPS has provided greatly increased interactivity and flexibility to the forecast centers in incorporating and visualizing data and constructing modeling and forecasting workflows.

Sacramento-Soil Moisture Accounting Model (Sac-SMA)

Sac-SMA is a lumped conceptual model that attempts to represent soil moisture characteristics to effectively simulate runoff that may be subsequently routed to become streamflow (Figure 6.2). Sac-SMA simulates six types of runoff, which can be further divided into fast- and slow-responding processes. In fast-responding processes, surface runoff is routed to a channel within hours and is typically driven by rainfall or

snowmelt events. Runoff that is characterized as fast-responding includes intensity-dependent surface runoff (i.e., runoff or snowmelt that exceeds the infiltration rate of unsaturated soils), runoff from impervious areas, and direct runoff (i.e., runoff after soils reach saturation). Slow-responding processes occur over porous areas and account for interflow, supplemental baseflow (e.g., water that drains from soils up to two months after an event), and primary baseflow (e.g., water that drains from soils over the course of years and sustains perennial flow during dry periods).

Within Sac-SMA, the soil is represented by two vertical zones to capture soil moisture processes near the surface as well as groundwater processes deeper within the soil column. Soil moisture within the upper zone is influenced by fast-response processes, and lower zone soil moisture is influenced by slow-response processes. Water can be stored and exchanged between the two soil zones; if the volume of water input to the model exceeds the modeled soil capacity, or if the rate of water input exceeds transport rates defined in the model, then water is available to the channel as runoff.

Sac-SMA model parameters are determined through calibration (see below) and define several quantities of the Sac-SMA's conceptual representation of physical soil processes. Among the parameters are the size and rate of soil moisture zones and transport, the percentage of water destined for deep aquifer storage, and land cover characteristics such as the impervious nature of an area, or amount of area covered by riparian vegetation.

Simulated soil moisture within the model can be characterized by tension or free water, and can be present in both lower and upper soil zones. Tension water may only be removed through evapotranspiration. Free water may be removed through evapotranspiration, percolation, and interflow. Lower-zone free water can be further characterized as supplemental or primary. Primary water drains slowly and describes baseflow over long periods of times, on the order of months to years. Supplemental water is more readily available to runoff than primary water and typically drains in the weeks to months following an event, augmenting primary baseflow. Each type of modeled soil moisture (tension, supplemental, and free) have defined maximum capacity values dictating how much water can be held at any given point.

Soil moisture transport rates are also defined through the model calibration process and determine how quickly water can move between zones and as interflow. Percolation is a function of lower zone dryness and upper zone free water content. The percolation rate influences how much water becomes surface runoff or interflow from the upper zone during a storm event and how much water is stored in the lower zone that can become available at a later time as baseflow.

SNOW-17

Since Sac-SMA effectively assumes that all precipitation reaches the surface as liquid water, a separate model is needed to represent snow and snowmelt for regions like the Colorado River Basin, in which snowmelt is an important component of overall runoff. SNOW-17, like Sac-SMA, is a lumped conceptual model that requires only precipitation and temperature to model snowpack accumulation and ablation. The model characterizes precipitation as rain or snow based on temperature and freezing level information and builds or melts a snowpack in response to these forcings. While the SNOW-17 model is relatively simplistic compared to models that rely on an energy balance and significantly more forcing data, it consistently performs well and often better than more complex snow energy-balance models (e.g., Franz, Hogue, and Sorooshian 2008).

Since temperature is used as a proxy for incoming solar radiation in SNOW-17, there are times when SNOW-17 may not melt snow at the rate observed. For instance, during cloudy warm days, the model may melt snow too quickly—in reality, cloud cover will inhibit incoming solar radiation, resulting in slower melting. When dust is covering snowpack (i.e., dust-on-snow conditions), the rate of modeled snowmelt may be too slow—in reality, the lower snow albedo results in the increased absorption of solar energy and quicker melt. In operations, such model inaccuracies may be corrected through adjustments to model parameters such as the melt factor.

Other snow-related products used by the CBRFC, and the snow simulation itself, are described further in Chapter 5.

Model setup and general use

The modeling units in CHPS consist of basins on the order of 10–1000 km². This allows for efficient calibration during the model development phase, and for examining and iteratively updating model forcings (e.g., temperature and precipitation data), states, and outputs in real time during the forecasting process. An example of this lumped approach is provided in Figure 6.10.

The primary models for an individual basin are SNOW-17 coupled to the Sac-SMA model, along with a routing function such as the Lag/K or unit hydrograph. The models embedded within CHPS provide a broad array of additional analytical and interactive functions, including model calibration, state updating, and post-processing, all accessible via an interactive interface.

The modeled Colorado River Basin is divided into about 400 basins, each having 1–3 elevation zones, which are simulated in a workflow that proceeds each day from the headwaters to the basin outlet, correcting obvious deficiencies in meteorological inputs and model behavior, basin by

basin, and accounting for known and estimated impairments, including storage operations, diversions and consumptive uses. The Upper Basin and Lower Basin models are run at 6-hourly and 1-hourly time steps, respectively, with the latter reflecting the flashier hydrologic response times in the Lower Basin.

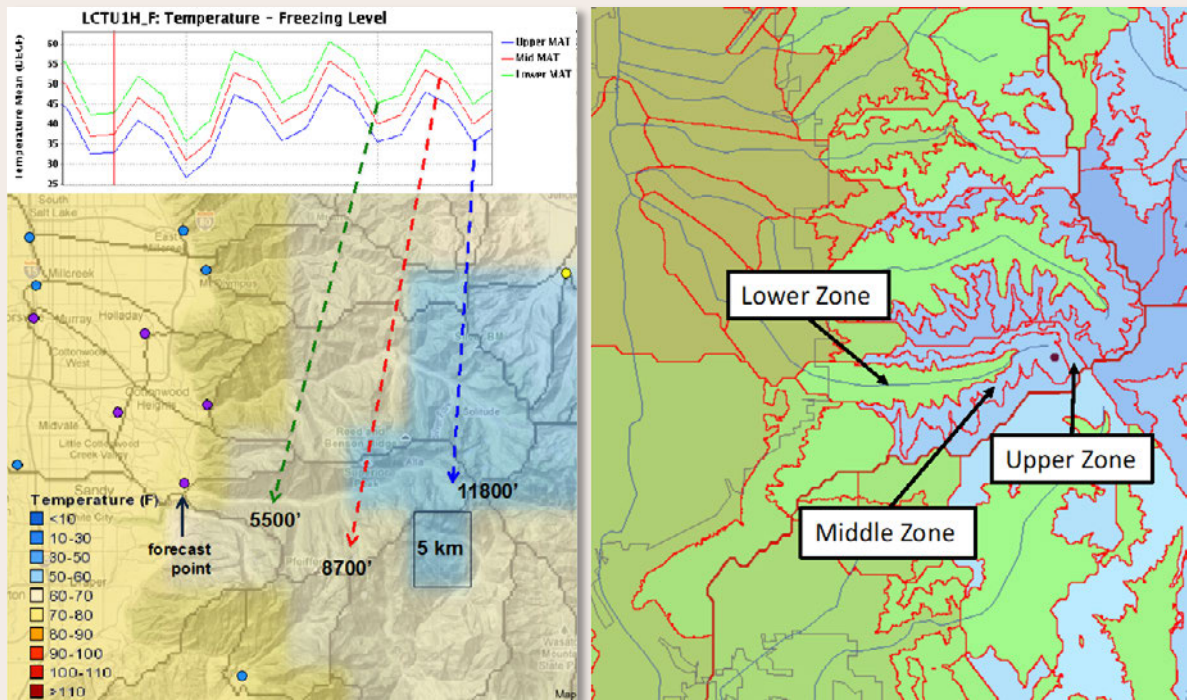


Figure 6.10

Illustration of the NWS traditional lumped approach to watershed modeling for the Little Cottonwood River canyon outside of Salt Lake City, Utah (right). The effect of elevation on temperature over the 6000+ foot terrain range is reflected in the mean areal 6-hour temperature forcings (left, top) that are developed for each of three elevation zones applied for the watershed of forecast point LCTU1 (right). Precipitation forcings and model parameters are also distinct for each zone. The elevation zones are not necessarily contiguous. A 5-km resolution gridded temperature analysis revealing similar gradients is shown for comparison (left, bottom). (Source: A. Wood, NCAR)

CHPS is designed for interactive use by forecasters. During critical times, forecasters use a myriad of methods to obtain data to enhance their awareness of the evolving dynamics in the basin, even beyond automated data systems. Phone calls to reservoir operators or to stream gauge operators such as the USGS can clear up any questions about measured flows, while intake of satellite snow information can inform snow cover fraction, and even viewing webcams of certain road locations can add insight about whether precipitation is falling as snow or rain at different locations. RFC forecasters use a combination of manual and automated

techniques to correct input data, going beyond the scrutiny already given to that data by the source agencies.

The SNOW-17 and Sac-SMA models as implemented by RFCs are well-known for being highly calibrated, and they currently offer the best performance in simulating streamflow down to sub-daily time-scales. Their application in forecasting also contains the most comprehensive use of information about impairments to the natural hydrologic system, even while many uncertainties remain in those data (Chapter 5). The optimized, conceptual nature of the models, however, gives rise to concerns about their ability to represent both evolving climate and weather patterns, and to represent changes in land cover, such as from fires, dust-on-snow, beetle kill, or changes in the seasonality of vegetation due to warming. Depending on the scale of these landscape disturbances, changes to the model can be made to account for hydrologic impacts; for instance, after a large, severe, fire, the impervious area within a basin may be adjusted to simulate increased runoff due to the presence of hydrophobic soils. Their reliance on fixed PET (which is not required, but is the configuration in which they are implemented) argues against their use for long-term projection without modification to the PET scheme.

Calibration

A long-standing and critical part of the RFC implementation of SNOW-17 and Sac-SMA has been model calibration. This includes extensive effort to develop or obtain records of impairments that affect streamflow, such as diversions and reservoir operations. Biases of no more than a few percent are common, and unlike other models used in the basin, calibrations are updated when forcings change (e.g., when the WMO climate normal period, currently 1981–2010, advances each decade), or more frequently. Some RFCs contract model calibration out to consulting companies such as RTI and more recently, Lynker, which have nationwide contracts with NWS that include this service.

Model calibration in the Colorado River Basin has been performed manually at the RFCs and for research studies, with the objective of minimizing errors in streamflow simulation. For the NWS models, observational datasets providing *a priori* parameters are the starting point (Koren, Smith, and Duan 2003; Anderson, Koren, and Reed 2006; Schaake et al. 2006). Algorithms for automated, objective parameter estimation have also long existed in the NWS calibration software in the form of the Shuffled Complex Evolution (SCE) single-objective optimization method (Duan, Sorooshian, and Gupta 1994). SCE usage in RFCs is mixed, however, with the general view being that it can provide an improvement over *a priori* parameters but does not perform so well that further manual tuning is not required. In recent decades, numerous parameter optimization algorithms have been introduced and are accessible in multi-method software

packages such as Ostrich (Matott et al. 2013) but these are not yet used by the RFCs.

Variable Infiltration Capacity (VIC) model

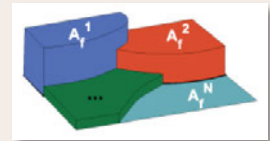
VIC is a grid-based, macroscale, semi-distributed physical land surface model (LSM) that solves full water and energy balances. VIC was developed at the University of Washington (Liang et al. 1994), and in its various forms has been applied to most of the major river basins around the world. Development and maintenance of the current official version of the VIC model is led by the Computational Hydrology group in the Department of Civil and Environmental Engineering at the University of Washington. The VIC model is an open-source development project that is now in its 5th major version; every new application addresses new problems and conditions that the current model may not be able to handle, spurring further development and iteration. Further information on the VIC model is available on a [website](#) hosted by the University of Washington Computational Hydrology Group.

Model setup

The VIC model is run at nominal grid resolution (e.g., 12-km or 1/8th degree dimension grid cells) but attempts to represent sub-grid variability in vegetation and elevation. VIC is regarded as a column model, which means that water cannot flow laterally, and the soil column in most applications is divided into three to five soil layers (Figure 6.4). Physical equations are used to simulate water and energy flows throughout the model. For example, evapotranspiration is calculated based on the Penman-Monteith equation (Penman 1948; Monteith 1965), soil drainage in the saturated zone is described by Darcy's law, and surface runoff in the upper soil layer is calculated based on the variable infiltration curve (Zhao et al. 1980). In addition to these processes, VIC simulates runoff in the upper surface layer and the release of baseflow from the lowest soil layer. Surface and base flow are subsequently routed by a separate routing model along the stream network to the basin outlet. Snow is represented in several forms: as a surface snow pack, as snow in the vegetation canopy, and as snow on top of lake ice when lakes are represented. More recently, VIC physics have been expanded to include ponded water, rudimentary glacier melt and migration, and frozen soils.

The land surface in VIC is modeled as a grid. VIC represents sub-grid variability in vegetation and elevation by partitioning each grid cell into multiple land cover and elevation classes. Inputs are sub-daily meteorological time series of air temperature, precipitation, radiation, and wind speed. Land-atmosphere interactions and water and energy balances at the surface are simulated at a daily or sub-daily time step. Water can only enter a grid cell via the atmosphere, and once water reaches the

Variable Infiltration Capacity (VIC) Macroscale Hydrologic Model



Link:

<https://vic.readthedocs.io/en/master/>

channel network, it is assumed to stay in the channel, i.e., it cannot flow back into the soil.

Calibration

Regional calibration remains a longstanding challenge in hydrologic modeling. The VIC models used in the Colorado River Basin are infrequently calibrated due to the expense. The last official calibration is believed to have occurred in 2004 (Christensen et al. 2004; J. Prairie, *pers. comm.*). In that study, VIC was calibrated on the Reclamation natural flows published at that time for three points in the basin: Green River at Green River, UT, Colorado River at Cisco, UT and Colorado River above Imperial, AZ.

Originally, the VIC models were calibrated manually as part of efforts to develop both climate change impact assessments (Christensen et al. 2004) and mid-range (seasonal) ensemble streamflow forecasting (see Chapter 8). The most recent calibrations were made using an automated multi-objective parameter estimation software package called MOCOM (Yapo, Gupta, and Sorooshian 1998).

Since the calibrations were last completed in the mid-2000s, the VIC model source code has evolved. In particular, the internal forcings-related code derived from MTCLIM (Running and Thornton 1996) has been upgraded. This code translates input of daily temperature minima and maxima, precipitation, and wind speed into sub-daily forcings for different elevation zones. These changes altered the simulated flow, in some cases by 20–30%, which is documented for locations included in the BCSD5 technical memo (Reclamation 2014).

The continued usage of VIC for water supply studies without sufficient effort to recalibrate and calibrate more extensively is a real concern, as a degraded calibration can significantly affect projected streamflow changes. Many of the basin studies conducted by Reclamation around the West have included new VIC calibration efforts, but not the Colorado River Basin Study (Reclamation 2012c). For the Colorado River Basin Study, a newer version of VIC was not recalibrated, though it was validated: it was run with historical climate to evaluate how well the new VIC version simulated the 29 natural flow points used by Reclamation (J. Prairie, *pers. comm.*). The results of this effort are published in Reclamation (2012c), page B4–3.

Model enhancements are typically developed by grant-funded projects in the small number of universities that have adopted VIC for hydrologic research. Like many models, VIC is not bug free and improves over time as bugs are found and fixed. As VIC versions change, and the forcings used to drive VIC are upgraded, the model itself is not always recalibrated to maintain streamflow simulation performance, which tends to degrade in the face of these changes. To support climate change work in the early 2010s, such as the CMIP3 hydrology projections effort, Reclamation

assembled existing VIC model configurations and mosaicked them into a West-wide domain, but without significant recalibration (Reclamation 2011).

More recently, after the CMIP5 hydrology projection effort, Reclamation and the U.S. Army Corps of Engineers have funded research into improving VIC model regional calibration (e.g., Mizukami et al. 2017). One of the problems of the CMIP5 VIC modeling involved spatially distributed VIC parameters: parameter tuning done by each region results in patchy spatial artifacts that cause spatial patterns in the simulations. Mizukami et al. (2017) focused on testing a new Multiscale Parameter Regionalization (MPR; Samaniego, Kumar, and Attinger 2010) approach that had been successfully demonstrated for a different land surface model. The VIC MPR results did achieve seamless parameter fields (by design) versus a patchwork of individual basin parameter fields, but results often did not equal or exceed the individual basin calibrations. The simulations from this study are available, but not for further practical application (N. Mizukami, *pers. comm.*).

Simulation biases from models including, but not limited to, VIC has motivated new Reclamation projects to develop methods for bias correction of outputs—particularly streamflow—that may be required in order to provide a confident simulation under current and historical climate, against which future projections of streamflow can be evaluated. Because bias correction is often a prior step in climate downscaling, when applied to streamflow it is often referred to as secondary bias correction.

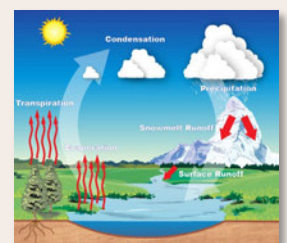
National Water Model (NWM)

The NOAA National Water Model, or NWM, is a next-generation hydrologic modeling and forecasting platform first launched in 2016. The NWM is notable because it represents a first attempt to implement very high resolution watershed process-oriented models for operational forecasting across the entire U.S., yielding forecast outputs on 2.7 million different stream and river reaches. The NWM is operated by the NOAA Office of Water Prediction at the National Water Center, with input and feedback from the RFCs regarding the skill and usability of forecast products. The NWM is the latest NWS-led foray into distributed modeling to supplant the Sac-SMA and Snow-17 models for operational streamflow forecasting, following the decade-long effort to introduce the coarser Hydrologic Laboratory-Research Distributed Hydrologic Model (HL-RDHM) in the RFCs.

Model setup and use

In the NWM, the water cycle is simulated with mathematical representations of the different processes in a river basin, and how these processes interact. The representation of these processes, such as infiltration, snowmelt and the flow of water through soil layers varies with

National Water Model



Link:
<https://water.noaa.gov/about/nwm>

changing soils, elevations, vegetation types and other variables. Simulations of the interactions and stream responses, which can change very quickly due to spatial and temporal variability in precipitation, must be run on a high-powered computer or super computer to support decision makers who need a fast turnaround when, for instance, flooding potential is high.

The NWM runs four uncoupled simulations of current conditions with look-back periods ranging from 28 hours to 3 hours. The initial conditions for the model's forecast runs are provided by these simulations or analyses. Short-range forecasts are executed hourly over the CONUS. The NWM produces hydrologic signaling at a very fine spatial and temporal scale. It complements official NWS river forecasts, which are at approximately 4000 locations across the CONUS, and produces guidance at millions of other locations that do not have a traditional river forecast. The NCAR-supported WRF-Hydro system is the core of the NWM. The Noah-MP land surface model (LSM) is used by WRF-Hydro to simulate land surface processes.

The NWM provides a number of forecast products, including products termed short-range (0–2 days), medium-range (0–10 days), and long-range (0–30 days). The short-range forecasts are deterministic single-value forecasts; the medium-range forecasts are from a 7-member ensemble; the long-range forecast is an ensemble updated daily, based on inputs from the NCEP CFSv2 climate forecast system (Chapter 7). The NWM relies on a 1-km resolution implementation of Noah-MP (Niu et al. 2011) coupled with a 250-m terrain routing scheme (Gochis, Yu, and Yates 2015), and a bucket groundwater model. Thus, given the model classification scheme in Table 6.1, the NWM is a hybrid of a land surface model and an explicit watershed process model, in terms of the detail of its physics and its spatial resolution.

The NWM contains orders of magnitude more complexity in its process description and spatial resolution than the NWS models, but has not been demonstrated to yield sufficient performance to be suitable for most applications of interest for water management in the Colorado River Basin, including short-range (1–10 day) and mid-range (seasonal) forecasts. Its heavy computational demands have also limited its ability to be directly calibrated, to provide seasonal water supply forecasts, especially in ensemble mode, and to be used for long-range projection. The NWM's optimal use at present appears to be flash-flood prediction, which benefits greatly from its ability to route streamflow through a high-resolution (250 m, 2.7 million-reach) channel network. The flash flooding application is less compromised by the deficiencies of the hydrologic simulation, because the intense rainfall rates and saturated hydrologic conditions lead to more straightforward rainfall-runoff relationships.

NWM calibration

The NWM was first implemented as an uncalibrated prediction system, but has since been subjected to several rounds of calibration effort. In contrast to the computationally cheaper VIC and RFS models, only parts of the NWM domain can be directly calibrated. Parameters are estimated using the Dynamically Dimensioned Search algorithm (Tolson and Shoemaker 2006) for small unimpaired basins and then distributed to the larger domain using concepts of ecological similarity. This approach has led to some improvement in NWM performance, but performance in basins not directly calibrated still lags considerably behind the NWS models.

6.4 Challenges and opportunities

Strong progress has been made over the last few decades in hydrologic modeling, including improved observations, scientific understanding, model process representations, and computing power and efficiency. In the Colorado River Basin, hydrologic modeling has primarily centered on the NWS models for operational short-range to mid-range (seasonal) forecasting, and the VIC land surface model for mid-range forecasting, trend and variability analysis, and climate change impact projection. These modeling capabilities under current practices have limits, and there are opportunities to advance beyond those limits, through improved meteorological inputs, better parameter estimation and calibration schemes, and development or adoption of new modeling platforms. These opportunities are summarized below.

Challenge

The conceptual modeling approach used in operational forecasting is not well-suited to take full advantage of advances in process understanding and modeling. The process-complexity of the models used for short-range to seasonal forecasting could be increased, albeit in a careful manner. This must be done within a strategy that acknowledges and provides for commensurate changes in operational workflows, including the development of data assimilation approaches.

Opportunity

- Implement a testbed framework for operational modeling that can incrementally advance and benchmark modeling improvements for different objectives, evaluating and justifying increases in complexity based on model performance.

Challenge

Distributed regional parameter estimation remains a vexing scientific challenge, and there is a critical need for accessible, efficient model calibration approaches to avoid the use of semi-calibrated land surface models in water supply applications (e.g., climate-change impact

assessment). Without this capability, no model will perform well, and watershed-tuned conceptual models will be hard to outperform.

Opportunity


- Multiscale Parameter Regionalization (MPR) offers promise but will require more development to leverage both the strengths of the attribute-based parameter development and the greater optimization potential in individual basins. Improved understanding of parameter sensitivities in models such as VIC, multi-objective calibration (considering more variables than just streamflow), and broader use of geophysical attributes, may offer near-term paths for improvement.

Challenge

The widespread use of VIC and similar land surface models for climate change impact studies may have inadvertently limited the exploration and quantification of projected hydrologic changes (Chapter 11). There is a need to identify processes that are not represented in models such as VIC and that lead to hydrologic impacts that affect stakeholders (such as dust-on-snow, Chapter 5), and to require that models used in climate-change impact studies a) include parameterizations to represent those processes, and b) demonstrate that their process performance is realistic.

Opportunity

- New models and modeling frameworks such as SUMMA, Noah-MP, WRF-Hydro, and CTSM may offer a more flexible foundation for enhancing model process complexity in appropriate, and carefully benchmarked ways. Process parameterizations in individual models may be leveraged to expand the range of options in flexible model frameworks. This activity will ideally be deliberate, pursuing targeted model improvements and motivated by stakeholder needs assessments, rather than top-down or wholesale adoption of an alternate off-the-shelf model.

An aerial photograph of a mountainous region, likely the Colorado River Basin. The terrain is rugged and brownish, with a prominent river valley cutting through the center. The river is dark and winding, surrounded by steep, rocky slopes. The overall scene is a mix of natural beauty and geographical complexity.

Volume III

Short-term and Mid-term—Informing the 1-Month to 5-Year Time Horizon

Chapter 7. Weather and Climate Forecasting

Chapter 8. Streamflow Forecasting

Volume III of the Colorado River Basin State of the Science report focuses on models and methods for forecasting weather, climate, and streamflow at the short- to mid-term time scale. Forecasts at this time scale are critical to water managers ensuring supply to their customers, farmers making planting decisions, ski areas planning staffing needs, utility operators making purchasing decisions, and retailers trying to plan inventory, among many others.

The two chapters in Volume III offer comprehensive descriptions and assessments of the state of short-to-mid-term forecasting methods, their skill, the data they require, their applications, and their tradeoffs. Results from weather and climate forecasting models feed into streamflow forecasting models to generate forecasted inflows for Reclamation's three primary models.

Chapter 7 describes the methods used to forecast weather and climate. The chapter is organized around the three forecast time frames: weather, 1-14 days; sub-seasonal, 14 days to 3 months; and seasonal, 3 months to 1 year. Weather forecasts are the most skillful of the three, and demonstrate steady, if small, improvements. The most challenging of these time frames is the sub-seasonal time frame; this chapter describes why this is so, and addresses the constraints on future improvements to forecasts on this time frame. Seasonal forecasts perform in the middle—they currently lack skill, particularly for precipitation, but judicious use of these forecasts, at times and places of good predictability, could be beneficial. Accordingly, the bulk of the chapter provides background on the tools and techniques that are behind seasonal forecasts and provides a good reference on the operational seasonal forecast products. The chapter concludes by describing the implications of the current state of seasonal forecasting for the basin, particularly the Upper Basin, and describes

initiatives to improve seasonal forecasts. Finally, it surveys the challenges and opportunities for forecasting across all three time frames.

Chapter 8 describes the concepts, approaches and tools used to forecast streamflow. This chapter focuses mainly on techniques and models that are relevant to Reclamation operations and planning activities—the monthly to seasonal ensemble forecasts that provide critical input to Reclamation’s 24-Month Study (24MS) and Mid-term Operations Probabilistic Model (MTOM), which are used to generate system operations projections (monthly reservoir releases and storages) up to 5 years out (Chapter 3). The chapter explains the sources of predictability, in order to provide a basis for forming priorities for improvement of forecasts. It describes three types of forecast models, dynamical, statistical, and hybrid; two types of forecasts, single-value and ensemble; and two forecasting paradigms, in-the-loop and over-the-loop. It provides detailed descriptions of operational forecast systems and experimental products across three time frames: short-range (days), mid-range (months) and interannual to decadal (Year 2 and beyond). Then, the use of mid-range streamflow forecasts—the only operational use of streamflow forecasts by Reclamation in the basin—in the 24MS and MTOM is described. Reclamation has considerable immediate interest in improving operational forecasts for Year 2, but decadal climate prediction currently exhibits poor skill, and NWS has not yet made investments toward improving Year 2 predictions. Chapter 8 describes Reclamation’s own initiative toward improved Year 2 forecasts, the Colorado River Basin Streamflow Forecast Testbed, intended to provide an objective approach to compare current and experimental streamflow forecasting methods. Finally, Chapter 8 provides a comprehensive review of the benefits, limitations, and challenges of a broad array of potential scientific and technological improvements to the existing operational streamflow forecast systems.



Chapter 7

Weather and Climate Forecasting

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Key points

- Uncertainty about upcoming weather and climate conditions translates into a major source of uncertainty in seasonal streamflow forecasts.
- Weather forecasts out to 10 days have relatively high skill and are progressively improving; they are incorporated into the CBRFC's operational streamflow forecasts.
- Sub-seasonal (2 weeks to 12 weeks) and seasonal (3 months to 1 year+) climate forecasts have much lower skill, especially in the Upper Basin, and they are not incorporated in the CBRFC streamflow forecasts.
- A major research effort has ramped up in the last decade to advance sub-seasonal and seasonal forecasting.
- Sub-seasonal and seasonal forecasts for temperature are generally more skillful than forecasts for precipitation, and skill for both is generally higher for the Lower Basin than for the Upper Basin.
- For precipitation, the Climate Prediction Center's seasonal forecast skill in both basins has been positive for winter and spring, suggesting users should focus their forecast use on those seasons.
- There are other opportunities to better utilize the skill that does exist in sub-seasonal and seasonal climate forecasts, such as using them to “nudge” the streamflow forecast ensemble during post-processing.

7.1 Overview

Uncertainty about future weather and climate affects streamflow forecasting on multiple timescales. In particular, uncertainty about the future weather and climate is one of the largest sources of error in seasonal streamflow forecasting. Even if, on April 1, we had perfect knowledge of the snowpack, and knew exactly how much of that snow would be translated into runoff, we would still have considerable uncertainty in spring-summer streamflow forecasts, because the weather that occurs from April through July can have a substantial impact on the runoff over that period.

When weather and climate forecasts have positive skill, i.e., predictive value above and beyond a null forecast (i.e., the climatological average conditions), there is an opportunity to inform and improve streamflow forecasts, and to guide other water resource decision-making. Weather forecasts out to roughly 10 days have relatively high skill for both temperature and precipitation (Figure 7.1), so CBRFC operational water supply forecasts incorporate them, as described in section 7.3.

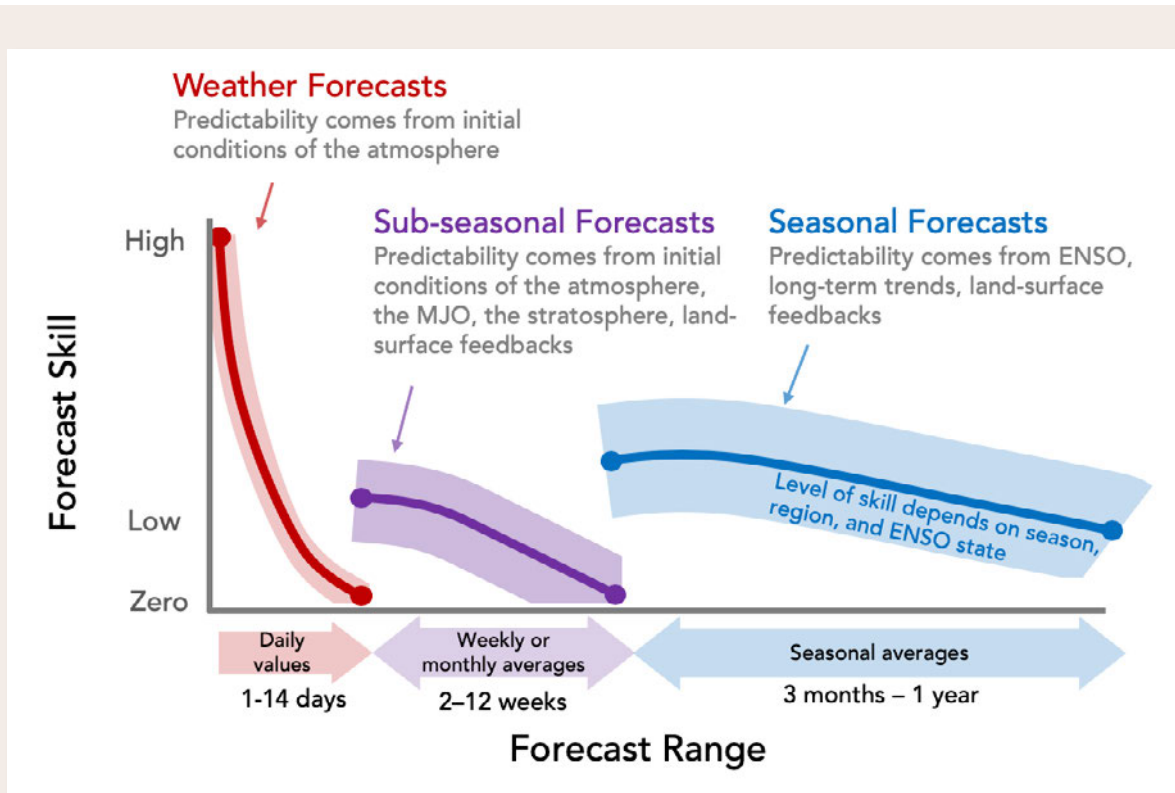


Figure 7.1

Schematic showing typical forecast skill relative to forecast range for three types of weather and climate forecasts: short-range weather forecasts; sub-seasonal climate forecasts, and seasonal climate forecasts, including potential sources of predictability. Relative skill is based on differing forecast averaging periods, shown inside the arrows. (Source: adapted from a figure by Elisabeth Gawthrop and Tony Barnston, International Research Institute for Climate and Society).

At longer sub-seasonal and seasonal climate forecast periods (>14 days), the forecast is generally much lower than the skill for weather forecasts, constraining opportunities for improving streamflow forecasts (Figure 7.1). The CBRFC operational water supply forecasts do not currently incorporate sub-seasonal (2–12 weeks) or seasonal (3 months and longer) climate forecasts, due to their low skill.

The CBRFC’s Hydrologic Ensemble Forecast Service (HEFS) system provides a pathway for incorporating additional weather and climate forecasts into their streamflow forecasts, if they have sufficient and consistent skill and an archive of historical hindcasts to allow validation. CBRFC forecasters have tested the incorporation of some sub-seasonal and seasonal climate forecasts, as described below and in Chapter 8.

The overall gap in predictive skill between weather forecasts and longer-term climate forecasts is reflected in fundamental differences in the way the forecasts are presented. First, weather forecasts are for specific daily

(or more frequent) outcomes, while sub-seasonal and seasonal climate forecasts are for outcomes as averaged across weekly, biweekly, monthly, or seasonal periods. Second, weather forecasts are usually presented as *deterministic* forecasts: a single temperature value or precipitation amount is forecasted. (The exception is the familiar “probability of precipitation” forecast, e.g., 40% chance of rain tomorrow.) Sub-seasonal and seasonal forecasts are typically presented in *probabilistic* terms, as a shift in likelihood compared to the historical distribution of outcomes, e.g., 60% chance of wetter than normal conditions over the winter season, compared to a 50% chance across the historical period (assuming a 2-category forecast). Sub-seasonal and seasonal forecasts can also be presented as deterministic forecasts (e.g., 2.3” of precipitation over the next 1-month period) but users should be aware that the specificity and precision of such forecasts is far greater than their accuracy and skill.

Increasingly, “S2S” is used as a shorthand for “sub-seasonal to seasonal forecasts,” but the actual forecast periods being referred to can be inconsistent. In most technical literature, S2S refers to sub-seasonal forecasts; i.e., forecast periods up to one season (<3 months). But S2S has also been used to refer to sub-seasonal *and* seasonal forecasts, or, less frequently, sub-seasonal *and* season 1 (i.e., 3-month) forecasts. To avoid confusion, in this chapter we use the terms “sub-seasonal” and “seasonal” instead of S2S, except when the latter is part of the name of a project.

7.2 What makes a weather or climate forecast useful?

First, a distinction needs to be made between forecast *quality*, which is assessed independently of the use of the forecast, and forecast *value*, which is the utility of the forecast to the user.

The assessment of forecast quality—verification—has several components. The measures of quality need to be evaluated across many (100s or 1000s) forecasts produced by the same forecast *system* in order for the measures to be taken as indicative of the quality of current or forthcoming forecasts that have not yet been verified (Hudson 2017), which is what the user really wants to know.

- *Accuracy* is the overall level of agreement between the forecasted and predicted values. But accuracy by itself can be misleading, since a “naïve” forecast can be quite accurate. For example, since precipitation occurs on only 20-30% of all days in most locations in the Upper Basin, a consistent daily forecast of “no precipitation” will be accurate 70-80% of the time.
- *Skill* is more meaningful than accuracy; it measures the accuracy of the forecast relative to a baseline “naïve” forecast: the climatological value,

a simple persistence forecast, or, if there are multiple forecast “bins,” the odds of forecasting the correct bin by chance alone. Positive skill (>0 for nearly all skill metrics) means that there is value beyond the naïve forecast. There are many different metrics of forecast skill; the metrics shown in the figures and tables below, and explained in the text, are the anomaly correlation (AC) and Heidke skill score (HSS). Both are fairly simplistic and cannot by themselves convey the multiple dimensions of forecast quality, or the forecast’s value to the user.

- *Reliability* is a measure of forecast quality specific to probabilistic forecasts; it is the agreement between the forecast probability and observed frequency of outcomes. For example, across all of the days a weather forecast system called for a 30% chance of rain, for perfect reliability it would have rained on 30% of those days, and so on for other percentages. Reliability can likewise be measured for sub-seasonal and seasonal forecasts; e.g., across all the 3-month seasons for which a climate forecast system called for a 60% chance of above-normal precipitation (assuming only two categories, above and below), then for perfect reliability, 60% of those seasons should have observed above-average precipitation, and so on.
- Additional measures of skill specific to probabilistic forecasts complement reliability. *Resolution* measures how well the forecasts can distinguish different categories; e.g., do the observed outcomes differ between periods with forecasts of 60% chance of above-normal precipitation and with forecasts of 70% chance of above-normal precipitation. *Sharpness* is the ability to forecast extreme values (probabilities near 0% or 100%) in at least some cases, rather than only values clustered around the observed mean probability.

Broadly speaking, the higher the forecast quality, the more opportunity there is for the forecast to be useful, but forecast quality and value to the user are not necessarily linked (Hudson 2017). Usefulness also strongly depends on the decision context, including the risk tolerance of the user, and whether the forecast is used in a decision-support tool (e.g., a streamflow forecast model) or considered on its own.

Deterministic weather forecasts out to 5–10 days have become skillful enough that the forecasted conditions can be treated as though they *will* occur, such as with the incorporation of weather forecasts into the CBRFC ESP water supply forecasts (see section 7.3). Water managers often use weather forecasts to make discrete, yes-or-no decisions with some confidence, e.g., releasing water from a nearly full reservoir now to avoid an uncontrolled spill a week from now, given the forecast of heavy rainfall over the next five days.

Sub-seasonal and seasonal climate forecasts will never have that level of skill or certainty; relatively low predictability at these time scales may be a fundamental property of the climate system (Albers and Newman 2019). But if climate forecasts have at least *some* positive skill or reliability for the basin and season of interest, they can potentially be useful. Since climate forecasts are typically presented in probabilistic terms, they are suited for modeling and decision support frameworks that are themselves probabilistic, such as ensemble streamflow prediction. In this case, the tendency shown in the climate forecast, if any (e.g., 60% chance of above-normal precipitation), can be used to weight the historical years used to populate the streamflow ensemble.

Climate forecasts can also be used to inform discrete, infrequent yes-or-no decisions, such as whether to generate hydropower during the fall and winter instead of maximizing water storage, but decision makers must accept the significant risk of the forecasted climate tendency not actually occurring (Garbrecht and Piechota 2005). Also, there may not be a large enough forecasted tendency in a given year or season to influence a decision. In many contexts, then, climate forecasts may provide more value when used selectively, rather than routinely.

7.3 Weather forecasts (1 to 14 days out)

The steady progress in weather forecasting over the last several decades has been called a “quiet revolution,” resulting from a steady accumulation of knowledge about the atmosphere and technical advances in modeling. Forecast skill for the mid-latitude regions in the Northern Hemisphere, such as over the Colorado River Basin, has been increasing by about 1 day per decade for forecast lead times of 3 to 10 days; today’s 5-day weather forecast is as skillful as the 4-day forecast was 10 years ago (Bauer, Thorpe, and Brunet 2015).

The main source of predictability and skill for weather forecasts is the accurate description of the initial conditions of the atmosphere (Figure 7.1) by coordinated global networks of observations from sensors that are land, ocean, and satellite-based, and from airborne sensors. Once initialized with those observations, the weather forecast model simulates the evolution of the initial synoptic (large scale) weather patterns shown in the observations. The skill of weather forecasts, on average, systematically declines from day 1 to day 14 (Figure 7.1) as the information contained in the initial conditions is gradually lost to chaotic processes underlying the motions of the atmosphere. This information loss can be slowed by improved initialization of the models (i.e., better observations), and by improved modeling of the physical processes, but a marked drop-off in skill during weeks 1 and 2 will persist through any conceivable future improvements. Producing moderately skillful forecasts at longer lead times

(i.e., sub-seasonal) requires additional information beyond weather patterns and associated atmospheric motions, such as the correct prediction of changes in the stratosphere, persistence due to land surface conditions, and slowly varying ocean-atmosphere patterns (e.g., Madden-Julian Oscillation, or MJO; and El Niño-Southern Oscillation, or ENSO).

All operational weather forecasts are based on dynamical, physics-based simulation models that run on supercomputers; thus, weather forecasting is also referred to as numerical weather prediction (NWP). The domain of most weather models is global, though very-high-resolution weather models (e.g., Weather Research and Forecasting model, WRF), with regional domains such as the western U.S., are also used for short-term forecasts of 48 hours or less.

The domain of all weather and climate models is gridded in three dimensions, with the vertical dimension representing multiple layers of the atmosphere. The models solve the fundamental physical equations for fluid motion; conservation of mass, momentum, and energy; and the ideal gas law. Many relevant processes occur at scales smaller than the model grid, such as cumulus cloud formation, so parameterization schemes are needed to properly describe the impact of these sub-grid-scale mechanisms on the large-scale flow of the atmosphere (Bauer, Thorpe, and Brunet 2015). The initialization of the forecasts with observations is accomplished through data assimilation, which typically involves the statistical correction of a prior short-term gridded model forecast to the newly available observations, in order to provide the most accurate gridded depiction of the initial state.

The primary global weather forecast models used in operational weather forecasts in the U.S. include the NOAA National Centers for Environmental Prediction (NCEP) Global Forecast System (GFS) model, the European Centre for Medium-Range Weather Forecasts (ECMWF) Integrated Forecast System (IFS) model (often referred to as the “European model”), and the Global Environmental Multiscale (GEM) model (the “Canadian model”).

The evolution of weather patterns over time is highly sensitive to the initial state of the atmosphere, and we cannot observe and describe those initial conditions perfectly. Consequently, it has become common to run a set, or ensemble, of weather predictions from the same model using slightly different initial conditions. The spread of the forecasts in the ensemble thus captures the uncertainty due to our imperfect knowledge of initial conditions. The NOAA Global Ensemble Forecast System (GEFS) based on the NOAA GFS forecast model is made up of 21 separate forecasts (ensemble members), with output four times a day and forecasts going out to 16 days. The ECMWF Ensemble Prediction System comprises 51 forecasts

from the ECMWF forecast model using different initial conditions, like GEFS, and also with slightly different model equations to represent uncertainty due to model structure and parameters (see discussion of uncertainty in Chapter 1).

Even with recent technical progress, these ensemble prediction systems for weather (and climate) forecasts inevitably have some bias (the forecasted mean is different from the observed mean) and unreliability (the forecasted distribution is different from the observed distribution). Thus, statistical post-processing of “raw” forecasts, to improve ensemble forecast guidance prior to its dissemination, is a critical element of the forecast process. The discrepancies between past forecasts and observations are used to adjust the raw real-time forecasts.

Skill of forecasts over weather timescales

Table 7.1 shows the skill of weeks 1 and 2 forecasts of precipitation and temperature for the Upper and Lower Basins from the NOAA NCEP CFSv2 (Climate Forecast System) model. The skill metric (Anomaly Correlation Coefficient; ACC) compares the 14-day average forecasted precipitation and temperature with the observed 14-day averages. As noted earlier, and shown in Figure 7.1, the skill drops off rapidly within that 14-day period, and the skill would be substantially higher if the results were only for week 1.

Table 7.1

Skill (Anomaly Correlation; AC) for weeks 1–2 (1–14 days out) of deterministic forecasts from the CFSv2 model for the calendar year (annual) and the climatological seasons, based on reforecasts for the 1999–2010 period. A perfect forecast would have an AC skill of 1.0; the climatological average has a skill of 0. The skill scores for the eight HUC4 sub-basins each in the Upper Basin and Lower Basin were averaged to produce the scores shown here. The CFSv2 forecasts were bias-corrected using quantile mapping. (Data: S2S Outlooks for Watersheds; <http://hydro.rap.ucar.edu/s2s/>)

Skill (AC) for Weeks 1-2 forecasts, CFSv2 model						
Variable	Basin	Annual	DJF	MAM	JJA	SON
Precipitation	Upper Basin	0.59	0.70	0.56	0.51	0.57
	Lower Basin	0.67	0.77	0.59	0.58	0.58
Temperature	Upper Basin	0.77	0.74	0.78	0.77	0.79
	Lower Basin	0.80	0.79	0.81	0.74	0.80

The forecast skill is generally high (about 0.6–0.8), with overall higher skill for temperature forecasts than precipitation forecasts. This disparity in forecast skill between temperature and precipitation is seen across longer time scales as well, which reflects that temperature varies less than precipitation over both time and space, and is also more straightforward to simulate and predict. Table 7.1 also shows that Lower Basin precipitation forecasts are somewhat more skillful than those for the Upper Basin, and that precipitation forecast skill in both basins is higher in winter than in other seasons. Predictive skill for precipitation also has strong seasonal patterns; skill is highest in winter, reflecting that the primary mechanism of precipitation (mid-latitude cyclonic storms) is broader scale and better simulated than convective precipitation in the warmer seasons.

CFSv2 is a fully coupled climate forecast model that incorporates the GFS weather forecast model (run at lower resolution than for weather forecasting) to represent atmospheric motions, an ocean model, and the Noah land surface model (Chapter 6). We show the skill of CFSv2 for weather timescales (weeks 1–2), instead of that of the GFS or another dedicated weather forecast model, to allow direct comparison with the skill (i.e., ACC) of the same CFSv2 model over sub-seasonal timescales (weeks 3–4) later in this chapter (Table 7.2). The skill of the operational GFS model over this time period would be higher than CFSv2 due to its higher spatial resolution and more optimized capture of initial conditions.

As mentioned above, the skill of weather forecasts has been increasing at a fairly constant rate over the past 20 years, as many improvements have been made in observing systems, assimilation schemes, and the models themselves. There may be an opportunity for CBRFC streamflow forecasts to incorporate weather forecasts, especially for precipitation, at longer lead times than is currently done.

Current use of weather forecasts by the CBRFC

Currently, the CBRFC ESP water supply forecasts that are key inputs to the 24MS and MTOM models (Chapter 3) use two types of weather forecasts: the 10-day quantitative temperature forecast (QTF) and the 5-day quantitative precipitation forecast (QPF). The temperature forecasts come from the National Blend of Models (NBM), a nationally consistent suite of calibrated forecast guidance based on a blend of both NOAA and non-NOAA weather model data. The precipitation forecasts are based on the NBM and additional guidance from the NOAA Weather Prediction Center. The forecast grids are modified by the CBRFC to allow for their incorporation into the CBRFC streamflow forecast model (Chapters 6 & 8).

The QPF predicts a specific, most-probable amount of precipitation that will fall over the forecast period; i.e., it is presented as a deterministic forecast. Because these short-term forecasts of precipitation have high

skill, the CBRFC forecast model treats the QPF as though it represents precipitation that has already fallen. When a storm is forecasted to hit the basin within 1–5 days from the issuance of an ESP or official streamflow forecast, the forecasted storm as shown in the QPF will cause an increase in the forecasted seasonal streamflow volume, even though the storm has not yet arrived. Likewise, if the QTF shows an unusually warm period in mid-winter, the CBRFC model can reduce the modeled lower-elevation snowpack and thus decrease the forecasted streamflow volume. Thus, over the course of a season, a trace created by the most-probable ESP forecasts incorporating the QPF (and QTF) consistently leads, by up to 5 days, a trace created by ESP forecasts without the QPF, while having similar fluctuations reflecting storms and melt episodes (Figure 7.2).

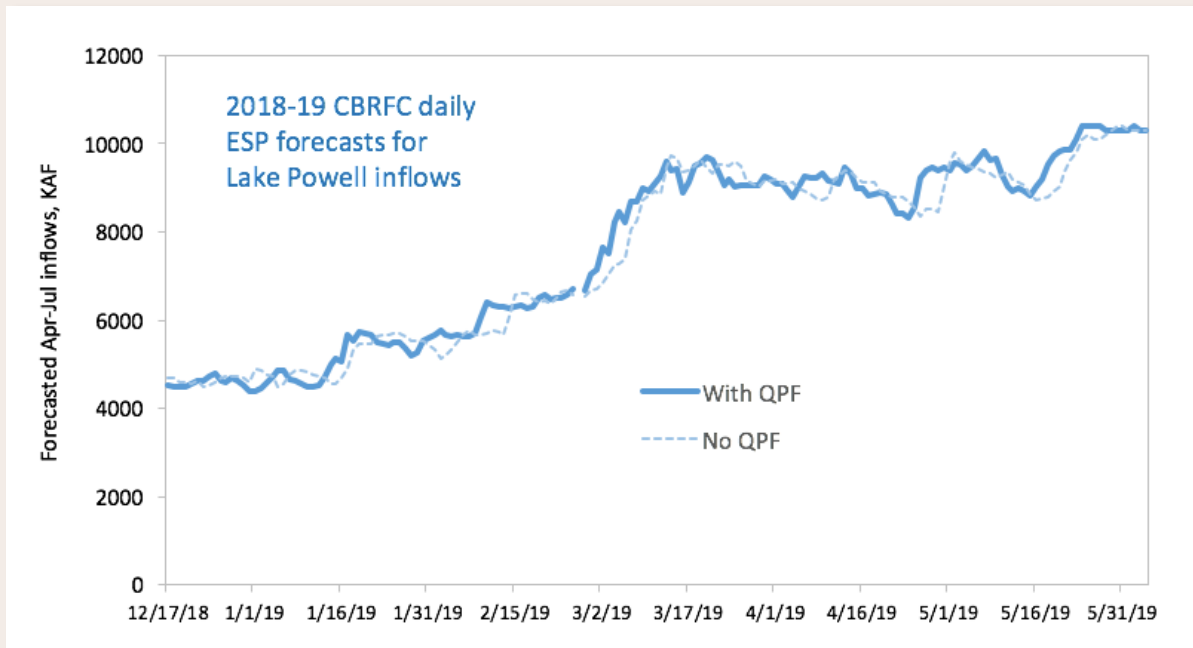


Figure 7.2

CBRFC daily ESP forecasts for April–July Lake Powell inflows for the 2018–2019 season issued from mid-December through early June. The default forecasts (“With QPF”) that incorporate 5-day Quantitative Precipitation Forecasts (QPF) and 10-day Quantitative Temperature Forecasts (QTF) show increases in forecasted streamflow volumes about 2–5 days before forecasts with no QPF, reflecting the expected gains from forecasted storms that have not yet occurred. (Data: CBRFC)

7.4 Sub-seasonal forecasts (2 weeks to 12 weeks)

Overview

For the purposes of this section, “sub-seasonal” refers to forecasts of meteorological variables at lead times from 2 weeks to 12 weeks in the future. This period has been called the “weather-climate prediction gap” (Mariotti, Ruti, and Rixen 2018). Short-term weather forecasts depend crucially on the initial state of the atmosphere that is input to the forecast models, while longer-term seasonal climate forecasts leverage predictability that emerges from the slower-evolving components of the Earth system including the ocean state, soil moisture, sea-ice conditions and other so-called “boundary conditions” for the atmosphere (Figure 7.1). The sub-seasonal prediction gap—where both initial and boundary conditions can be important—is being closed, albeit slowly, from both sides. The first two months of seasonal climate forecasts provides information about this time frame, while medium-range weather prediction models such as NOAA’s GFS and the ECMWF’s IFS are being extended out to 30–45 day forecasts and beyond.

The dynamical models used for sub-seasonal (and seasonal) predictions are typically run at lower resolution than for weather forecasts. They simulate the interactions between the atmosphere, ocean, land surface, and sometimes sea ice components of the climate system. While it is common to differentiate “climate models” from “weather models,” these two categories overlap a great deal, especially for the models used at a sub-seasonal time scale—some of which are also used for weather forecasts, while others are also used for multi-decadal climate projections (i.e., GCMs; Chapter 11).

When current generation weather forecast models (e.g., GFS, ECMWF IFS) are extended beyond 14 days, they develop large systematic forecast errors, particularly in their representation of tropical convection and the positioning of the mid-latitude jet stream and storm track (World Meteorological Organization 2013). Similarly, climate forecast models such as NOAA’s CFSv2, which are better tuned to reduce bias in the climatological (long-term average) atmospheric circulation, tend to have lower performance for short lead times (0–7 days) than the weather models. This lower performance is due to many factors: coarser spatial resolution, biases that appear in the oceanic and land surface components, and the fact that the atmospheric and oceanic initial conditions are not optimized as they are for weather models. An active area of research is to better incorporate data from the atmosphere, land, ice, and oceans into the initial conditions of forecast models, referred to as “coupled data assimilation” (World Meteorological Organization 2017).

Sub-seasonal forecasting also faces a statistical disadvantage compared to seasonal forecasts. Because the forecast periods for the sub-seasonal forecasts are shorter than the 3-month season that is the typical period for seasonal forecasts, there is less time for the unpredictable component of the climate (“noise”) to be averaged out.

Note, also, that sub-seasonal forecast skill quoted for periods such as “weeks 1–2” or “weeks 2–3” will be dominated by the weather forecast skill for the early part of that period (Figure 7.1). The same is true for the Climate Prediction Center (CPC) revised monthly forecasts that are issued with no lead time, i.e., on the last day of the month preceding the forecasted month, as opposed to the initial forecasts issued with 8–14 days lead time (See “NOAA CPC Outlooks” below).

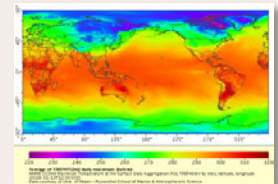
Sub-seasonal forecasts of temperature and precipitation are inherently suited for probabilistic interpretation and analysis. Accordingly, ensembles of numerical weather and climate prediction model forecasts are the tools of choice. Such ensembles may be generated by multiple runs of a single forecast model, which accounts for the uncertainty due to our imperfect knowledge of the initial state of the atmosphere. Ensembles can also be comprised of multiple runs from different models, such as with the North American Multi-Model Ensemble (NMME); in this case the ensemble also captures the uncertainty due to model structure and parameters, similar to the CMIP (Coupled Model Intercomparison Project) ensembles of multi-decadal climate projections (Chapter 11). The NMME, which is used for both operational sub-seasonal and seasonal forecasting consists of seven models in total: CFSv2, two Canadian models (CanCM4 and GEM-NEMO), two NOAA GFDL models (CM2.1 and FLOR), NCAR’s CCSM4, and NASA’s GEOS S2S. Studies have shown that the ensemble-average forecasts from NMME are more skillful than those from any single model in the ensemble (Becker, Van den Dool, and Zhang 2014; Kirtman et al. 2014).

An effort to generate and archive real-time and retrospective ensembles of sub-seasonal forecasts (SubX; Pegion et al. 2019), similar to NMME, is described below under “Other activities to improve sub-seasonal forecasts.”

Sources of predictability

The past decade has seen much progress in identifying and quantifying potential sources of sub-seasonal prediction skill (Vigaud, Robertson, and Tippett 2017), fueling a broad and active research program on sub-seasonal forecasting (e.g., National Academies 2016; World Meteorological Organization 2013). For the continental U.S., the potential sources of skill with the most promise are the tropical Madden-Julian Oscillation (MJO) (Stan et al. 2017), stratospheric variability, and land-atmosphere coupling, including the role of soil moisture. The identification of these phenomena is

NMME Models and Variables Summary



Link:

<https://www.ncdc.noaa.gov/data-access/model-data/model-datasets/north-american-multi-model-ensemble>

important because improvement in their representation in climate models can lead to improvement of sub-seasonal temperature and precipitation forecasts. A technical overview of the current state of the science is found in the volume edited by Robertson and Vitart (2019).

The MJO is a large area of enhanced convection (i.e., thunderstorms) in the tropical Indian and Pacific Ocean that generally moves from west to east (Zhang 2013 and references therein) and recurs with an irregular 40–70 day time period. Numerical models have limited success at forecasting the progression of convection associated with the MJO. Some of the strongest associations of the MJO with precipitation in the United States are seen in California and along the west coast of the U.S. during the wintertime (Zhou et al. 2012), including an effect on atmospheric rivers (Guan et al. 2012). While the impacts of the MJO in the interior West are less than those on the West Coast, the storms of early March 2019 demonstrated that atmospheric rivers can bring substantial precipitation to the Colorado River Basin.

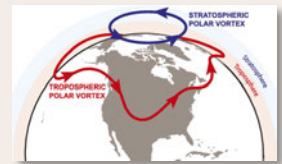
Certain stratospheric phenomena have also been identified as a potential source of skill for weather forecasting on sub-seasonal scales (Robertson and Vitart 2019). The stratosphere is the layer of the atmosphere that lies above the troposphere and is very stable, that is, resistant to vertical motions such as convection. In the mid-latitudes, the lower boundary of the stratosphere lies at about 10 km above the surface, but this boundary can be as high as 20 km in the tropics and as low as 7 km in the polar winter. There are two stratospheric phenomena of particular interest for sub-seasonal prediction: the quasi-biennial oscillation (QBO) in the tropics, where the winds above the tropical tropopause change direction in a roughly 26-month repeating cycle, and variations in the stratospheric polar vortex, including stratospheric sudden warming (SSW) events. See Waugh, Sobel, and Polvani (2017) for a primer on the “polar vortex.”

It is hypothesized that the changing winds due to the QBO may modulate the ability of tropical convection to influence the mid-latitude storm track and hence precipitation over the western U.S. For example, there is some indication that the QBO along with the MJO (see above) may jointly provide increased skill in predicting atmospheric river activity (Mundhenk et al. 2018). For the polar SSWs, the influence is more directly felt on the northern edge of the storm tracks and there is empirical evidence that in the days and weeks after a SSW there is a greater likelihood of extreme cold events (Kidston et al. 2015). However, the surface influence of the SSW appears to be primarily focused in Eurasia and the eastern United States, not in the Colorado River Basin.

A better representation of the land surface and its interactions with the atmosphere is another potential source of forecast improvement on

What is the Polar Vortex and How Does it Influence Weather?

Waugh, Sobel, and Polvani (2017)



Link:

<https://journals.ametsoc.org/doi/10.1175/BAMS-D-15-00212.1>

sub-seasonal time scales, and one particularly relevant to the Colorado River Basin. Most attention here is focused on the role of soil moisture—both better estimation of the initial state of the soils, and better simulation of the evolution of soil moisture anomalies. For sub-seasonal forecasts, soil moisture has two primary effects: It can reduce surface temperature by directing more of the incoming solar energy to evaporation rather than heating, and it can serve as a source of moisture to the atmosphere (Koster et al. 2011; Dirmeyer and Halder 2016). The research has tended to focus on summer conditions as that is when the impacts of soil moisture are thought to be greatest. Indeed, the impacts of having accurate soil moisture conditions were shown to be primarily for temperature.

In the Colorado River Basin and arid West, including initial soil-moisture states in the forecast model enhanced sub-seasonal temperature forecast skill, particularly when soils were wetter than average (Koster et al. 2011). For precipitation, increased forecast skill by including soil-moisture states was seen in the upper Great Plains, but not elsewhere. Correlations also have been found between soil moisture and the onset of the North American Monsoon; the hypothesized mechanism is that wet soils delay the seasonal heating of the land surface which is necessary to drive the land-ocean temperature gradient that then initiates the monsoon (Grantz et al. 2007). Accordingly, better treatment of soil moisture in forecast models may benefit summer precipitation forecasts in the Lower Basin. Simulation of the snowpack in forecast models could also result in improved sub-seasonal to seasonal forecasts both due to the direct effect of snow on surface temperature, and to the delayed impact on soil moisture during and after the snowmelt season.

Finally, ENSO's influence is present on the sub-seasonal time scale, as well as on longer time scales (see Chapter 2). Convection in the tropical Indian and Pacific Oceans has a significant influence on precipitation and temperature in the western United States. Ocean temperature anomalies associated with ENSO also lead to tropical convection anomalies that in turn alter the position and activity of the storm track in the Pacific. While ENSO is usually associated with seasonal forecasts (see next section), it also influences the likelihood of temperature and precipitation anomalies on sub-seasonal scales. As detailed in Chapter 2, those influences are stronger in the Lower Basin than the Upper Basin.

Operational sub-seasonal forecast products

NOAA CPC outlooks

There are relatively few operational forecasts from NOAA in the sub-seasonal time frame, reflecting the less mature state of sub-seasonal climate forecasting relative to weather forecasting, and even relative to seasonal climate forecasting. They are described here. First, NOAA CPC

produces an operational, 2-category (above or below normal), probabilistic temperature outlook for weeks 3–4 (Figure 7.3, left). The outlook is based on a blend of dynamical forecast model output, including CFSv2, ECMWF, and the SubX model ensemble, as well as the statistical (or empirical) tools also used for the CPC seasonal outlooks (Table 7.3). Reforecasts may also be used to adjust model output.

The quantity shown in these maps (Figure 7.3) is interpreted as the probability of the average temperature for days 15–30 being above or below the 1981–2010 observed average for that two-week period. For locations where it is impossible to assign any odds, “EC” or “equal chances” is indicated. In contrast, the 6–10 day and 8–14 day outlooks, as well as the seasonal outlooks, are 3-category, tercile forecasts (above normal, near normal, and below normal). NOAA CPC also produces a two-category precipitation outlook for weeks 3–4 (Figure 7.3, right), but this outlook is labeled “experimental” because little skill has yet been demonstrated.

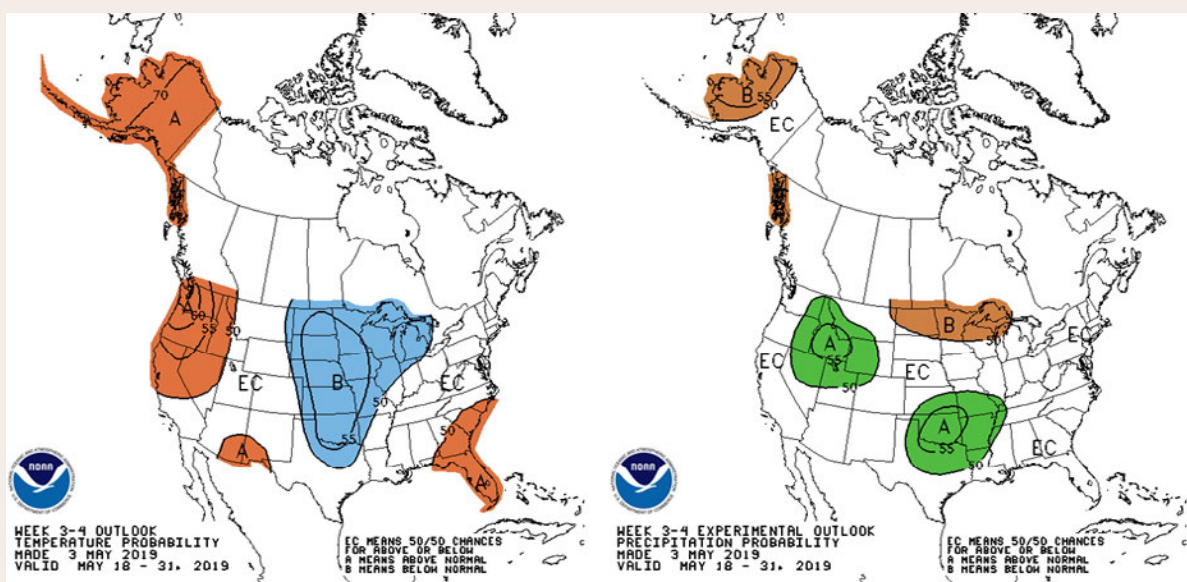


Figure 7.3

NOAA CPC operational 2-category (above or below normal) probabilistic temperature outlook for weeks 3-4 (left) and experimental 2-category (above or below normal) probabilistic precipitation outlook for weeks 3-4 (right). (Source: NOAA CPC; <https://www.cpc.ncep.noaa.gov/products/NMME/>)

NOAA CPC also produces operational 30-day temperature and precipitation outlooks (Figure 7.4), likewise based on a blend of dynamical forecast models (NMME ensemble—see next section; CFSv2 and ECMWF) and statistical tools and trends. These are issued mid-month, with a “valid” period starting at the beginning of the next month (0.5 month lead). With

that 2-week lead time, weather forecast skill is not included in the outlooks. Updated 30-day outlooks are issued at the end of the month (0-month lead), which do incorporate weather forecast information for weeks 1-2, though updated NMME information is not available.

Finally, a 90-day (3-month) average seasonal forecast is also made (as discussed in more detail in the next section), with a 2-week lead time (0.5 month lead). For each of these forecast periods, CPC provides a discussion of the reasoning behind each forecast, including factors such as the MJO and soil moisture, as well as a discussion of the guidance from dynamical models, including those archived in SubX.

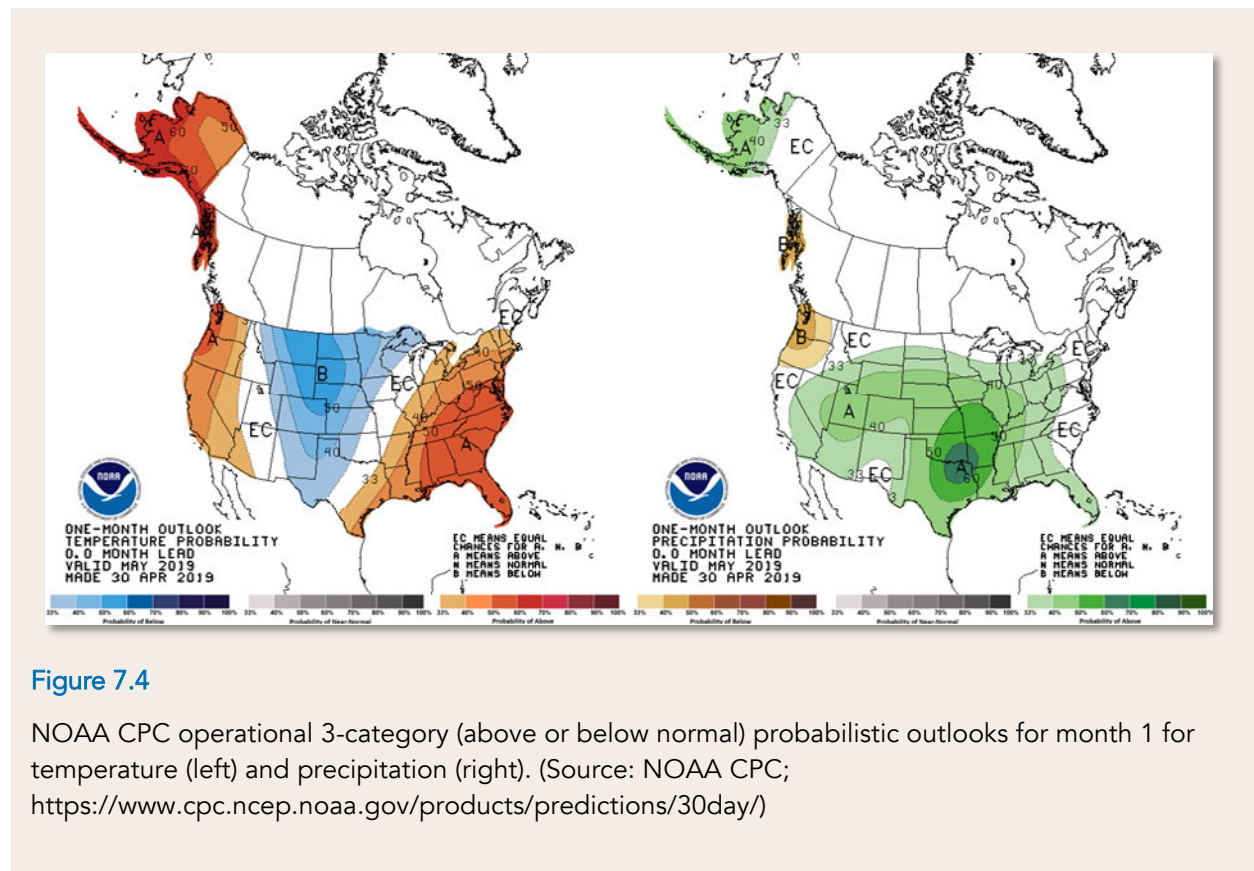


Figure 7.4

NOAA CPC operational 3-category (above or below normal) probabilistic outlooks for month 1 for temperature (left) and precipitation (right). (Source: NOAA CPC; <https://www.cpc.ncep.noaa.gov/products/predictions/30day/>)

Assessing forecast skill for sub-seasonal (and seasonal) forecasts

A single probabilistic forecast cannot, in general, be verified or falsified. But we can evaluate the performance of the forecast system by comparing a set of many forecasts over a period of years with observations, and by deriving statistical metrics of skill. These skill estimates are based on the performance of the forecast system in the past, or of a set of hindcasts that have been produced as if the current system had been operating over that period. This information can guide users about the expected performance of the forecasts of the future, but past performance is no guarantee of the same skill continuing into the future (Weisheimer and Palmer 2014).

In general, the skill of climate forecasts varies much more over space and time than does the skill of weather forecasts (Mariotti et al. 2020). Importantly, some seasons are more amenable to skillful forecasts than others, and this will be noted in the text and tables below. There has also been recent progress in identifying, in real-time, windows of opportunity during which climate forecasts are more likely to be skillful—i.e., times when there are particularly large events in the tropics (MJO, ENSO) or the stratosphere that are likely to have a large imprint in the weather of the extratropics, including the western U.S. (Albers and Newman 2019; Mariotti et al. 2020).

Skill of CPC week 3-4 forecasts for CONUS

Skill evaluation for the CPC weeks 3-4 operational outlooks is available only in aggregate for the conterminous United States (CONUS). In the Heidke skill score (HSS), 100 is a perfect forecast, -50 is a completely incorrect forecast, and a score above 0 indicates skill versus a random forecast. Over the 4-year period from September 2015 to May 2019, the Heidke skill scores for the CPC weeks 3-4 outlooks for CONUS averaged about 40 for temperature, and about 10 for precipitation.

Skill of CPC 30-day forecasts for CONUS and the basin

The skill of the CPC operational 30-day forecasts (at 0.5 month lead time) can be explored using CPC's interactive [Verification Web Tool](#). The skill (HSS) of the temperature forecasts CONUS-wide has averaged about 10 since 2015, though higher, averaging about 20, since 2005. The precipitation forecasts have had no skill, on average, since 2005 (HSS = ~0), with no improvement in recent years. Across the Upper Basin states of Utah, Wyoming, and Colorado, the 30-day temperature forecasts have been more skillful than for CONUS (HSS = 24 since 2005; HSS = 28 since 2015). The precipitation forecasts for Utah, Wyoming, and Colorado have been more skillful than for CONUS (HSS = 7 since 2005), and skill has not increased over time.

Skill of CFSv2 model forecasts for the Colorado River Basin

As described above, the CFSv2 model forecasts are one of the tools used as guidance for the CPC sub-seasonal forecasts. We show the skill of CFSv2 alone to allow comparison with the skill of the model over the weather forecast period (Table 7.1). In general, the AC skill of weeks 3-4 forecasts (i.e., for 15-28 days out) from the CFSv2 model is low (<0.2) for both precipitation and temperature in the Upper and Lower Basins (Table 7.2). Skill is generally lower in the Upper Basin, especially for precipitation (<0.1), perhaps reflecting the weaker ENSO signal there.

CPC Verification Web Tool



Link:
<https://vwt.ncep.noaa.gov/>

Table 7.2

Skill (Anomaly Correlation; AC) for week 3-4 (15-28 days out) forecasts from the CFSv2 model for the calendar year (annual) and the climatological seasons, based on reforecasts for the 1999-2010 period. The skill scores for the eight HUC4 sub-basins each in the Upper Basin and Lower Basin were averaged to the basin-wide scores shown here. The CFSv2 forecasts were bias-corrected using quantile mapping. (Data: S2S Outlooks for Watersheds; <http://hydro.rap.ucar.edu/s2s/>)

Skill (AC) for Weeks 3-4 forecasts, CFSv2 model						
Variable	Basin	Annual	DJF	MAM	JJA	SON
Precipitation	Upper Basin	0.09	0.09	0.07	0.11	0.10
	Lower Basin	0.16	0.18	0.11	0.13	0.14
Temperature	Upper Basin	0.16	0.22	0.03	0.22	0.18
	Lower Basin	0.18	0.23	0.10	0.23	0.21

S2S Climate Outlooks for Watersheds

The “S2S Climate Outlook for Watersheds” effort is a collaboration between NCAR, CU Boulder, Reclamation, and NOAA CPC to improve the understanding and application of sub-seasonal climate forecast products in the hydrology and water management sector, and to test the capacity to generate new forecast products (Baker, Wood, and Rajagopalan 2019). The [map-based web tool](#) (Figure 7.5) shows real-time forecasts from CFSv2 with additional post-processing, and also real-time forecasts from the NMME ensemble. (Again, CFSv2 and NMME output are key elements of the operational CPC weeks 3–4, monthly, and seasonal outlooks, but the CPC outlooks incorporate additional guidance.) Reforecasts have been generated from both sets of models to allow for verification and skill assessment.

The web tool displays deterministic (single-value) precipitation and temperature forecasts from CFSv2 for weeks 1–2, weeks 2–3, and weeks 3–4, and from the NMME for forecasts of 1-month periods at 3 different lead times: 0, 1 month, and 2 months. The forecasted values are expressed in anomalies to allow users to more easily assess whether conditions are expected to be above or below normal. The interface allows users to select any HUC4 watersheds, including the 8 sub-basins of the Upper Basin and the 8 sub-basins of the Lower Basin, and see the forecast values (and skill scores) specific to that watershed. The tool allows users to view the ensemble average of the NMME, as well as the seven model outputs

individually; toggling between the outputs of the individual models provides some sense of the uncertainty in the forecasts.

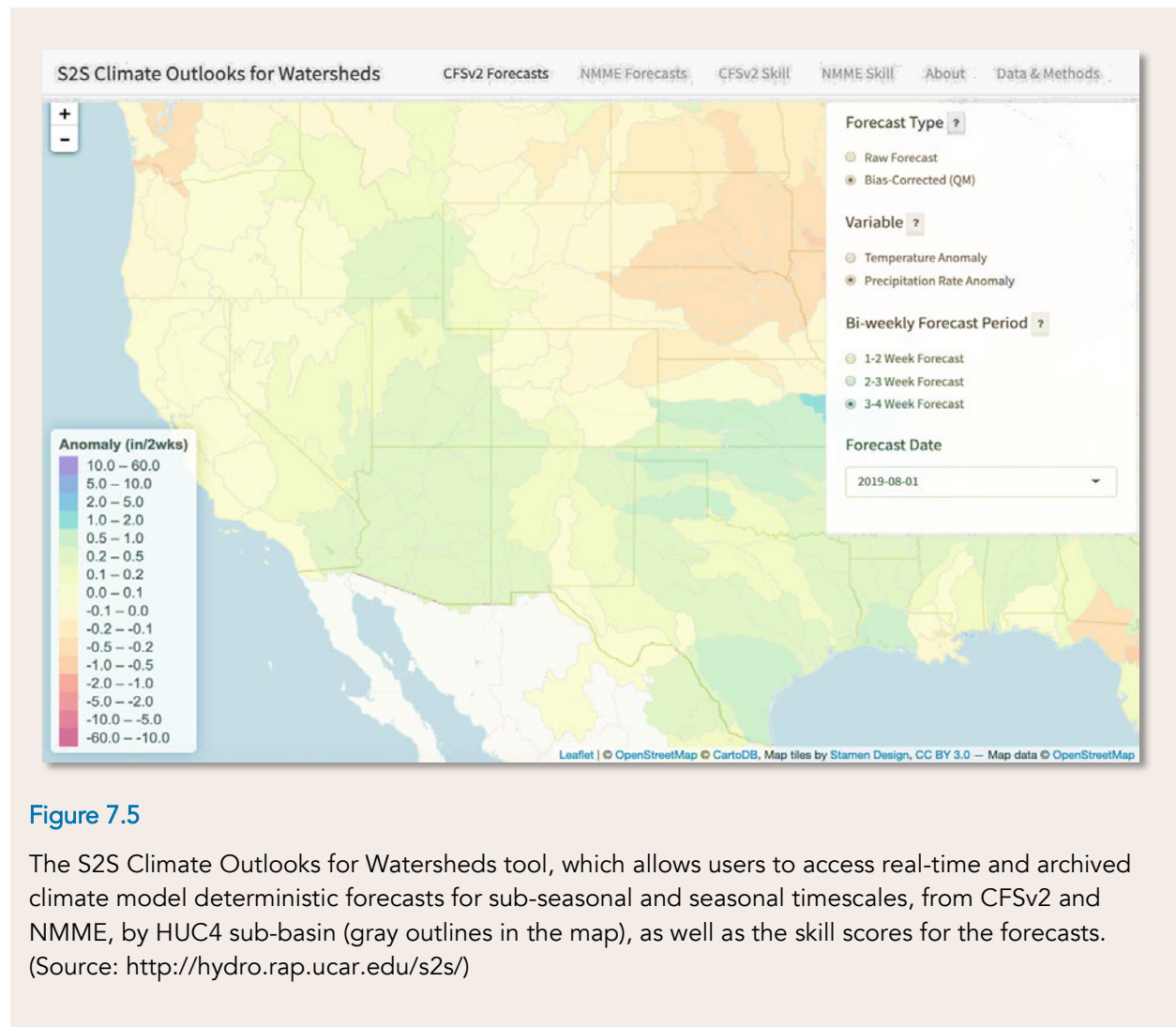


Figure 7.5

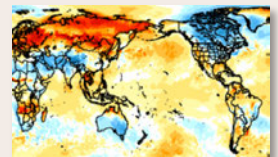
The S2S Climate Outlooks for Watersheds tool, which allows users to access real-time and archived climate model deterministic forecasts for sub-seasonal and seasonal timescales, from CFSv2 and NMME, by HUC4 sub-basin (gray outlines in the map), as well as the skill scores for the forecasts. (Source: <http://hydro.rap.ucar.edu/s2s/>)

Other activities to improve sub-seasonal forecasts and their use

SubX

The NOAA-funded Subseasonal Experiment (SubX) is a coordinated set of sub-seasonal prediction efforts and data archiving intended to explore the value of a multi-model ensemble for sub-seasonal forecasting (Pegion et al. 2019). This program was modeled after the NMME for seasonal forecasts (see next section). The SubX effort includes historical reforecasts (i.e., hindcasts) for 1999–2015 and real-time forecasts from seven modeling systems. Real-time forecast maps from the various models and from the multi-model ensemble are available on the SubX [website](http://cola.gmu.edu/subx/).

Subseasonal Experiment—SubX



Link:
<http://cola.gmu.edu/subx/>

Sub-Seasonal Forecast Rodeo

To promote the development of novel S2S forecasting methodologies, the Reclamation R&D program, in collaboration with NOAA and the California Department of Water Resources, held a Sub-Seasonal Forecast Rodeo from spring 2017 to spring 2018. Six teams of forecasters responded to an open public call and competed to produce the most skillful forecasts of temperature and precipitation across CONUS for weeks 3–4 (15–28 days out) and weeks 5–6 (29–42 days out). The forecasts were issued every two weeks for one year, with forecasts from the CFSv2 model used as a benchmark. Between one and three teams produced forecasts better than CFSv2, depending on the variable and lead time, with the most notable improvements seen in precipitation, for which CFSv2 showed almost no skill during the year-long contest period. (Note that in any given 1-year-period, CFSv2 and other forecast models and methods may significantly overperform or underperform relative to their longer-term skill, due to variability in the climate.) The methods of the winning teams will be made publicly available to potentially improve operational sub-seasonal forecasts. A second Sub-Seasonal Forecast Rodeo began in summer 2019.

S2S workshops

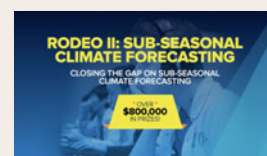
The Western States Water Council and the California Department of Water Resources have co-sponsored a series of workshops to further dialogue among western states' water agencies and Reclamation, NOAA, and the research community on improving S2S precipitation forecasting to support water management decision making in the western U.S. The most recent workshop, in May 2018, included presentations on the operational and planning needs for seasonal climate forecasting in the Colorado River Basin, the mechanisms of cool-season precipitation in the Upper Basin, and climate forecasting challenges in the Upper Basin in the context of CBRFC streamflow forecasting.

Implications for the Colorado River Basin

While there is active research in all the areas of untapped sources of skill, it is hard to anticipate what the combined effect of many incremental improvements will be, including general improvements in weather and climate models and coupled (land-atmosphere-ocean) data assimilation, which are ongoing and will continue. The goal of much of this research is to push the boundaries of skillful and potentially useful probabilistic weather prediction into weeks 3 and 4, and this is where advances in skill are most likely to come, albeit from a relatively low baseline at present (e.g., Table 7.2).

Likewise, it is unclear whether any of the proposed pathways to improve skill discussed above will result in improved sub-seasonal forecasts specific to the Colorado River Basin. Based on the current literature, there is an indication that the Lower Basin may benefit from forecast improvements

Forecast Rodeo II



Link:

<https://www.drought.gov/drought/forecast-rodeo-ii-leaderboard>

more than the Upper Basin. In particular, better representing combined effects of the MJO and QBO may improve precipitation forecast skill in the Lower Basin. The MJO is also known to modulate tropical cyclones in the eastern Pacific that occasionally cause heavy precipitation and flooding in the Lower Basin (Maloney and Hartmann 2000; Klotzbach 2014). It is plausible that the influence of the MJO on atmospheric rivers could, on occasion, affect the Upper Basin, but this has yet to be demonstrated. Improvement in treatment of the land surface and its influence on the atmosphere may lead to improvements in prediction of North American Monsoon precipitation that primarily affects the Lower Basin.

But even without significant improvements in overall forecast skill, there is still plenty of room to improve how the current skill of existing forecast systems is deployed by users of forecasts. The recent progress toward identifying “forecasts of opportunity” (Albers and Newman 2019; Mariotti et al. 2020) is a promising step toward more strategic deployment of sub-seasonal climate forecasts, i.e., consulting them in those locations, and during those seasons and specific times, when they are likely to have the most skill.

7.5 Seasonal climate forecasting

Overview and sources of predictability

The interest in predicting the climate on seasonal time scales to prepare for anomalous conditions is longstanding. The earliest published scientific effort in seasonal climate prediction was motivated by back-to-back failures of the Indian monsoon in 1876 and 1877 that caused a catastrophic drought (Blanford 1884). Blanford’s investigation found that an abundant spring snowpack in the Himalayas was counterproductive for the Indian monsoon later that summer—an early insight into seasonal land surface feedbacks.

The effort to understand and predict the Indian Monsoon also fostered research by Sir Gilbert Walker in the early 1900s into the “Southern Oscillation,” which is now understood as the El Niño-Southern Oscillation (ENSO) phenomenon (Chapter 2). A major breakthrough in the understanding of the functioning and influence of ENSO, and ultimately for seasonal climate forecasting, was the insight that ENSO was a coupled ocean-atmosphere phenomenon (Bjerknes 1966; 1969). It was later recognized that El Niño events resembled each other enough that it made sense to average them into a typical or canonical sequence (Rasmusson and Carpenter 1982). Such “compositing” became a key tool in unlocking the typical ENSO footprint of climate anomalies over North America (Ropelewski and Halpert 1987; 1989).

A general assumption in seasonal climate prediction is that the climate system displays preferred and recognizable patterns (footprints) that can be revealed through physical reasoning or statistical means. The search for analogues (Van den Dool 1994) is driven by the same notion that certain circulation patterns are more common than others, such as an enhanced southern winter storm track across the U.S. during El Niño. (CPC's empirical climate prediction methods that use the concepts of footprints and analogues is discussed in the next section.)

During the late 20th century, dynamical, fully physical climate models were increasingly run to simulate atmospheric conditions forced by (specified) anomalous sea surface temperature (SST) states to see whether the models could reproduce observed atmospheric behavior. As with short-term weather forecasts, the fast changing initial conditions in the atmosphere need to be captured to solve that portion of the forecast problem, while more slowly evolving conditions of the land and ocean were originally modeled as static boundary conditions (Gates et al. 1992).

Once it became clear that the modeled atmospheric behavior was realistic, the next step was to develop coupled ocean-atmosphere models that could be used to explore climate changes (i.e., GCMs; Chapter 11). These models were tested and refined by predicting ENSO events as well as seasonal climate anomalies (e.g., Becker, Van den Dool, and Zhang 2014; Bellenger et al. 2014; Weisheimer and Palmer 2014). These coupled Earth system models explicitly include evolving, rather than fixed, SST and land surface conditions. There are now more than a dozen coupled models that predict the state of ENSO in an operational manner, with highly variable, though overall positive, forecast skill (Barnston et al. 2012; 2017; Tippett et al. 2017). A key development in seasonal forecasting beyond ENSO was the discovery that global drought footprints of the swings of the Pacific Decadal Oscillation (PDO) and the Atlantic Multi-decadal Oscillation (AMO) could be reproduced in coupled climate models (Schubert et al. 2009), though this discovery has yet to pay dividends for the Colorado River Basin (Chapter 2).

The current predictability and skill in seasonal forecasts still comes mainly from those sources identified during the long history of seasonal forecasting: the tendencies associated with key modes of ocean-atmosphere variability, primarily ENSO, other slowly varying processes such as land surface feedbacks, and robust long-term trends (e.g., warming temperatures).

Operational seasonal climate forecasts from NOAA CPC

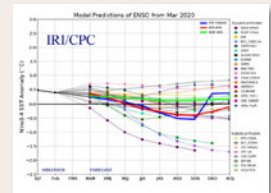
NOAA CPC and its predecessors have made a huge cumulative investment in developing and refining their seasonal forecasting methodology over several decades. While there are many other entities and individuals producing seasonal climate forecasts, ranging from the ECMWF to private

consulting firms, the CPC forecasts are the most widely used in the U.S., across a broad spectrum of users, including in water resources, and serve as a benchmark for other efforts.

Starting in 1995, CPC settled on the current framework of seasonal (3-month) forecasts (called “outlooks”) with multiple lead times out to 12.5 months. The two key ingredients supporting this framework were 1) the increasing community efforts to monitor and predict ENSO, as synthesized in a monthly updated [IRI ENSO “plume”](#) (Barnston et al. 2012); and 2) the development of the “Optimal Climate Normals” (OCN) methodology that takes advantage of longer-term climate variability and trends, whether linked to climate change or not. [The CPC seasonal forecasts](#) are released monthly, on the third Thursday of each month.

Figure 7.6 shows the January 2020 forecast for February–April 2020 (0.5 month lead time). These tercile forecasts are made in reference to the upper/middle/lower thirds of the 1981–2010 climatology (10 cases each), and the color shading shows tilts in the odds of one of the terciles in the climatological distribution (33%/33%/33%). For example, the darker brown shading for “B(elow)” in the precipitation outlook in Figure 7.6 means there is a 40–49% probability of seasonal precipitation for February–April being in the lower third of the historical distribution, compared to the

IRI/CPC ENSO Predictions Plume



Link:
https://iri.columbia.edu/our-expertise/climate/forecasts/ens0/current/?ens0_tab=ens0-sst_table

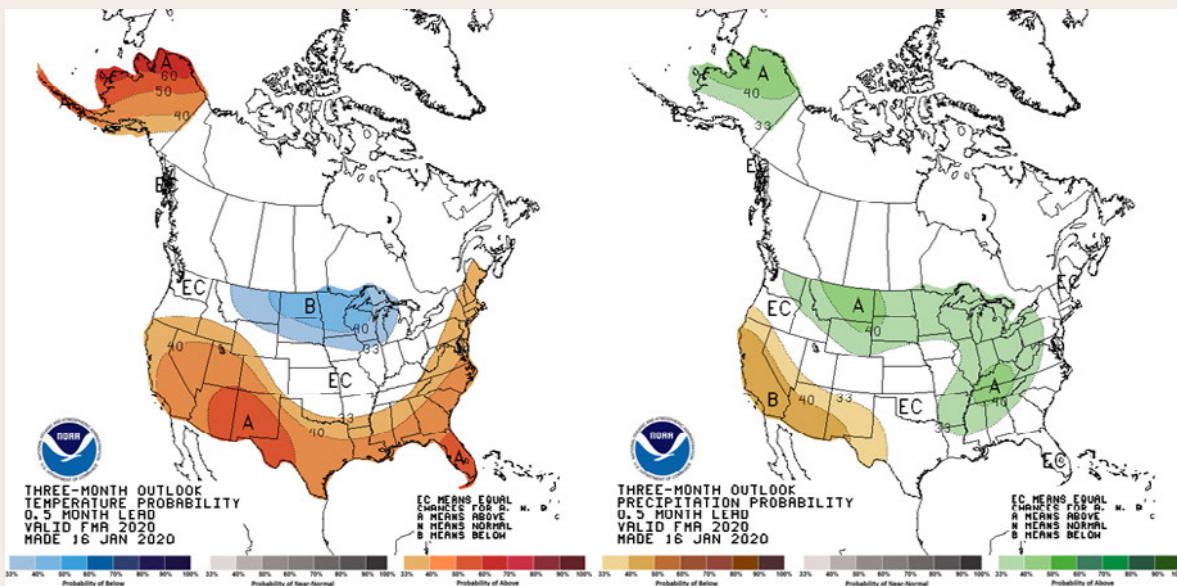


Figure 7.6

CPC seasonal outlooks for February–April 2020 for temperature (left) and precipitation (right), released on January 16, 2020. Darker shading shows tilts in the odds relative to the climatological (1981–2010) distribution of outcomes; see the text for further explanation. (Source: NOAA CPC; https://www.cpc.ncep.noaa.gov/products/predictions/long_range/)

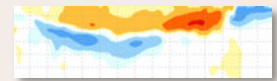
climatological probability of 33% for that outcome. If there is no appreciable tilt for any tercile, equal chances (“EC”) are assigned.

CPC also produces a weekly [ENSO status update](#), and an [ENSO blog](#); both can be helpful in interpreting the physical mechanisms behind the seasonal forecasts.

Forecast tools

CPC uses a broad suite of forecast tools for seasonal forecasts, comprising both empirical (statistical) models and dynamical climate forecast models (Table 7.3). The two most important empirical tools are based on ENSO and Optimal Climate Normals (OCN), respectively. The other tools are Canonical Correlation Analysis (CCA), Ensemble CCA (ECCA), Constructed Analogues (CA), and Screening Multiple Linear Regression (SMLR). These empirical tools and their predecessors were the only quantitative guidance used in CPC forecasts prior to 2005; the dynamical tools were added to the suite of guidance around 2006. CPC provides a short introduction to all tools [online](#).

ENSO: Recent Evolution, Current Status and Predictions



Link:

https://www.cpc.ncep.noaa.gov/products/analysis_monitoring/lanina/enso_evolution-status-fcsts-web.pdf

ENSO Blog

Link:

<https://www.climate.gov/news-features/department/enso-blog>

Table 7.3

Forecast tools used by NOAA CPC to inform their seasonal climate forecasts. Type: E = empirical; D = dynamical. The empirical tools that use multiple predictors (CCA, ECCA, CA, SMLR) are typically based on these four classes of predictors: 200mb global velocity potential (upper air flow information), global sea surface temperatures (SST), sea-level pressure north of 40°N, and U.S. soil moisture. (Source: NOAA CPC; https://www.cpc.ncep.noaa.gov/products/predictions/long_range/tools.php)

Forecast Tool	Type	Usual importance to forecasts	Contribution to forecasts	Comments	Reference
ENSO Composites	E	Higher	Typical climate “footprint” of the current or forecasted ENSO state	The mainstay of CPC seasonal forecasts	Higgins, Kim, and Unger (2004)
Optimal Climate Normals (OCN)	E	Higher	Recent (15-year) trends in temperature and precipitation, if different from longer-term (30-year) normal	During clear-cut El Niño or La Niña events, ENSO composites include OCN information in a single tool	Huang, Van den Dool, and Barnston (1996); Van den Dool (2007)
CFSv2 model	D	Higher	Physically based prediction of future climate conditions	Also included in NMME	Saha et al. (2014)

Forecast Tool	Type	Usual importance to forecasts	Contribution to forecasts	Comments	Reference
NMME model ensemble	D	Higher	Physically based prediction of future climate; ensemble shows uncertainty due to model structure; ensemble mean more skillful than any one model	Ensemble of 7 models: CFSv2 (NOAA); CanCM4i and GEM-NEMO (Canada); FLOR and CM2.1 (NOAA GFDL); CCSM4 (NCAR); GEOS S2S (NASA)	Kirtman et al. (2014)
Canonical Correlation Analysis (CCA)	E	Lower	Influence of multiple predictors of future climate conditions as captured in linear relationships		Barnston (1994)
Ensemble CCA (ECCA)	E	Lower	Same as above	Only used for temperature	Mo (2003)
Constructed Analogues (CA)	E	Lower	Same as above	Most useful when analogues are based on soil moisture	Van den Dool (1994; 2003)
Screening Multiple Linear Regression (SMLR)	E	Lower	Same as above	Refined version of MLR tools used by early forecasters	O'Lenic et al. (2008)

As mentioned before, ENSO information and OCN have been the primary tools since the 1990s; as new forecast tools were added, each needed to have a skill assessment using reforecasts. The dynamical coupled forecast models (CFSv2 and the NMME ensemble) were evaluated even more critically; they had to reproduce empirical ENSO results before being included as guidance. When the consensus among the different tools is strong, that information is used to tweak the odds in the forecasts (e.g., moving from a 40% to 50% probability for the wettest tercile). Particularly strong ENSO signals, or regional trends, like the warming trend in the western U.S., will tend to yield high “tilts” in the odds.

Operational skill of CPC seasonal forecasts

CPC has archived all 0.5-month lead forecasts since 1995 and their national skill scores are [online](#). The long-term (1995–2019) average Heidke skill score (HSS) for temperature has been 14, while the average HSS for precipitation has been 4, where 100 is perfect skill and 0 is no skill. As with sub-seasonal forecasts, seasonal forecasts in general are more skillful for temperature

than for precipitation. This disparity has been seen across the globe by different forecasting groups; e.g., Weisheimer and Palmer (2014)

(As described earlier in this chapter, Heidke skill is based on “hits”; if 20 of 60 seasonal forecasts “hit” for the correct tercile—as would be expected by chance alone—the skill score is 0; if all 60 are correct, the skill score is 100, and if none of them are correct, the score is -50.)

The skill of the CPC seasonal forecasts has been highly variable over time, with several periods during which the temperature forecasts had an HSS over 50 and precipitation forecasts had an HSS over 30. Conversely, there have been many periods of negative skill (<0), especially for precipitation. Most of the variation appears to correspond to the strength of ENSO events; when moderate to strong El Niño and La Niña events emerge, the ENSO forecast models generally perform better (Barnston et al. 2012), and the footprints of ENSO impacts on the western U.S. are more predictable. Livezey and Timofeyeva (2008) showed that most of the nationwide skill of the first decade (1995–2005) of seasonal CPC forecasts was due to the “Super El Niño” of 1997–98, the long-lived La Niña of 1998–2001, and other strong ENSO events. During periods when ENSO-neutral conditions prevail, seasonal forecasts in the U.S. are generally less skillful.

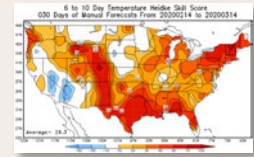
Regional skill in the Colorado River Basin

Skill of operational seasonal outlooks for the Colorado River Basin

The Upper Basin was identified early on as an area of relatively weak to non-existent ENSO signals in precipitation, compared to the ends of the ENSO dipole: El Niño wetness in the Southwest and La Niña wetness in the Northwest (Redmond and Koch 1991; see Chapter 2). Thus, CPC’s early ENSO-related forecasts often left the Upper Basin blank, or EC, except for the 1997–98 super El Niño. Wolter et al. (1999) uncovered more nuance in the ENSO signal, finding distinct seasonality in the Upper Basin’s response to ENSO.

Maps of skill for the CPC seasonal precipitation outlooks issued from 1995–2019 are shown in Figure 7.7, for the four 3-month seasons of the water year. For the Upper Basin, skill has been highest in late winter (JFM) and spring (AMJ), hitting Heidke skill scores of up to 20 along the southern periphery of the Upper Basin. In contrast, late summer and fall forecasts have shown no overall skill across the 1995–2019 period. For the Lower Basin, skill has been highest in late winter (JFM), with skill scores up to 40 in western New Mexico and at least 30 in nearly all of the Lower Basin. This seasonal peak in skill mainly reflects the footprint of ENSO events being expressed most strongly in late winter. There has been less skill or no skill in the other three seasons, except for northwestern Arizona in spring.

CPC Verification Summary



Link:

<https://www.cpc.ncep.noaa.gov/products/verification/summary/>

During the most recent decade (2010–2019) skill during late winter (JFM) over the Lower Basin has been higher than during the full period as shown in Figure 7.7. Also, during 2010–2019, skill during spring (AMJ) has been much higher in both the Upper and Lower Basins than during the full period. This recent performance may reflect improvements in the forecast system and thus might be expected to continue. Figure 7.8 shows maps of skill for the CPC seasonal temperature outlooks issued from 1995–2019, for the four, 3-month seasons of the water year. For both the Upper Basin and Lower Basin, positive skill is seen in all four seasons, with somewhat higher skill for the Lower Basin. The HSS is over 50 for large portions of the Lower Basin in all four seasons, and portions of the Upper Basin in spring and summer. Much of the skill in temperature outlooks in the western U.S. is due to the consistent increasing trends in seasonal and annual temperature, as captured in the OCN tool.

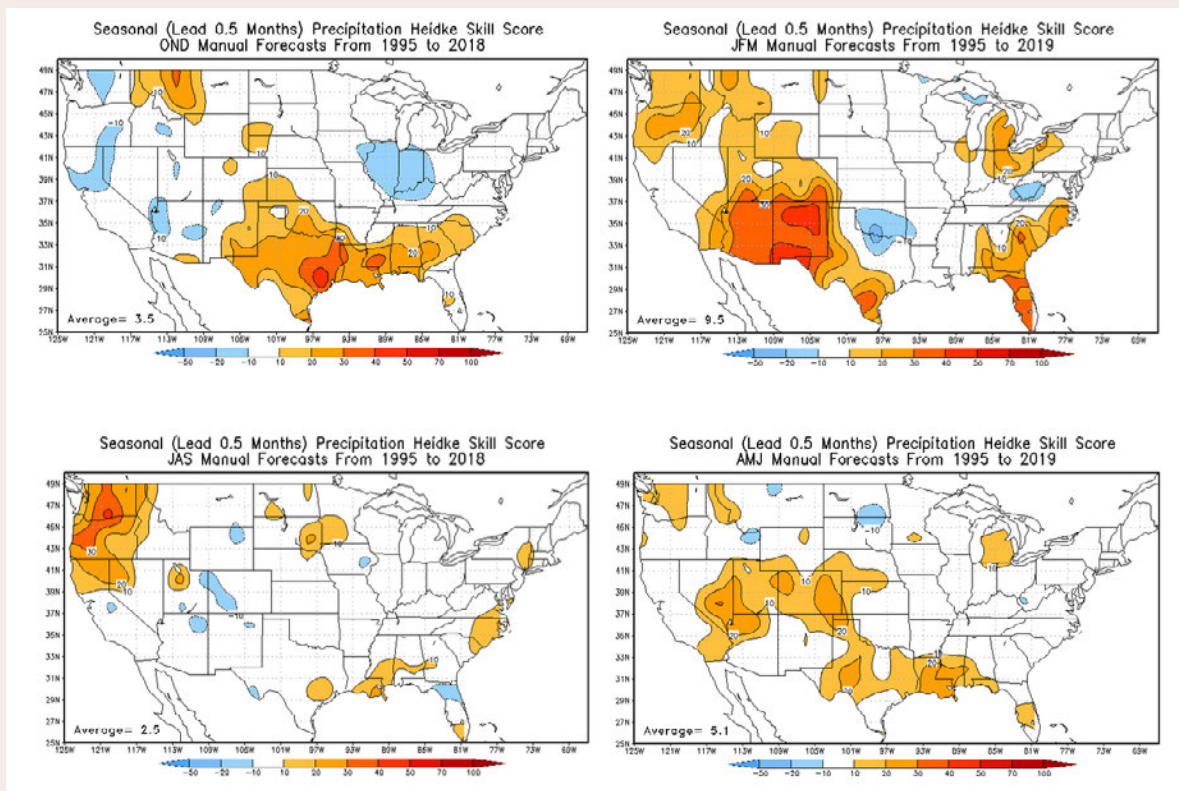


Figure 7.7

Maps of CPC seasonal precipitation forecast skill (Heidke Skill Score; HSS) from 1995–2019, using seasons that correspond to quarters of the water year: October–December (upper left); January–March (upper right); April–June (lower right); and July–September (lower left). Positive skill (orange colors) in the Upper Basin is limited to winter-spring (JFM and AMJ; (HSS=10-20). In the Lower Basin, positive skill is seen mainly in winter (JFM) and is higher (30–40) than in the Upper Basin. (Source: NOAA CPC; <https://www.cpc.ncep.noaa.gov/products/verification/summary/>)

Skill of NMME model forecasts for the Colorado River Basin

As described above, the NMME dynamical model ensemble is one of the tools now used by CPC forecasters to inform operational seasonal forecasts for the Upper and Lower Basin. In Table 7.4, the skill scores for NMME forecasts for season 1 (1–90 days out) are shown for the Upper and Lower Basin. As with the sub-seasonal model forecasts from NMME and CFSv2, temperature is forecasted more skillfully than precipitation, and the Lower Basin seasonal climate is more skillfully forecasted than in the Upper Basin.

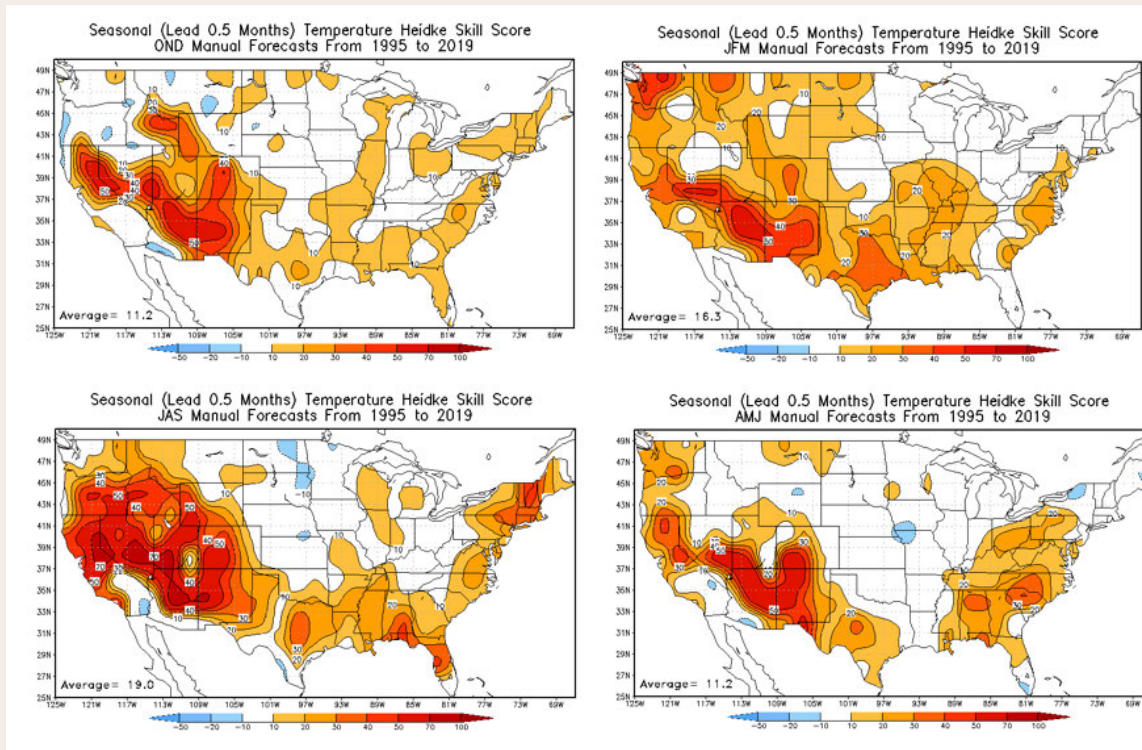


Figure 7.8

Maps of CPC seasonal temperature forecast skill (Heidke Skill Score; HSS) from 1995–2019, using seasons that correspond to quarters of the water year: October–December (upper left); January–March (upper right); April–June (lower right); and July–September (lower left). Positive skill (orange and red colors) is seen in both the Upper Basin and Lower Basin in all seasons, with the highest overall skill in late summer (July–September). (Source: NOAA CPC; <https://www.cpc.ncep.noaa.gov/products/verification/summary/>)

Table 7.4

Skill (Anomaly Correlation; AC) for Season 1 (1–90 days out) forecasts from the NMME forecast ensemble (7 models, including CFSv2) across the calendar year (annual) and for the climatological seasons, based on reforecasts for the 1981–2010 period. The skill scores for the eight HUC4 sub-basins each in the Upper Basin and Lower Basin were averaged to the basin-wide scores shown here. (Data: S2S Outlooks for Watersheds; <http://hydro.rap.ucar.edu/s2s/>)

Skill (AC) for Season 1 forecasts, NMME ensemble						
Variable	Basin	Annual	DJF	MAM	JJA	SON
Precipitation	Upper Basin	0.19	0.19	0.29	0.11	0.15
	Lower Basin	0.27	0.41	0.28	0.09	0.20
Temperature	Upper Basin	0.19	0.12	0.25	0.24	0.20
	Lower Basin	0.31	0.28	0.31	0.30	0.36

As with the operational CPC forecasts—which incorporate the NMME along with other guidance (Figure 7.7)—the NMME results in Table 7.4 indicate that predictability in seasonal precipitation is greater in the winter and spring than in the summer and fall, with a spring peak in the Upper Basin and winter peak in the Lower Basin—which is helpful, since the former two seasons best correspond to snowpack accumulation and water-year runoff. However, even in winter and spring, seasonal forecast skill is still relatively low.

Activities to improve seasonal forecast skill in the Colorado River Basin

SWcasts—precipitation outlooks for the interior Southwest

Since ENSO only explains a fraction of seasonal climate variability in the interior Southwest (Utah, Colorado, New Mexico, Arizona), and since SNOTEL information was not incorporated into climate divisions (nor CPC forecasts), Wolter (2002) embarked on an effort in the late 1990s to create statistical seasonal forecasts (SWCasts) that increased the pool of predictors beyond ENSO, and improve the temperature and precipitation predictands by including SNOTEL data (Chapter 5). To create forecast zones within the 4-state region, SNOTEL and weather stations were grouped into core regions using statistical analyses to select the most similar ones, with one set of 6–10 regions each for four meteorological seasons.

For potential predictors, previously established teleconnection indices (e.g., ENSO indices, North Atlantic Oscillation, etc.), as well as tropical Pacific or

Indian Ocean, and Gulf of Mexico SSTs were considered. Some predictors had been discovered a century ago, such as key sea-level pressure regions in the Pacific and Indian oceans. Inspired by Knaff and Landsea (1997) and similar to O'Lenic et al. (2008), SWcasts employs Screening Multiple Linear Regression (SMLR) as a statistical forecast tool. Over the following 16 years of forecasts, the balance of “hits” versus “misses” was sufficiently positive to translate into positive skill scores. During this period, forecast skill for the Upper Basin (in CO and UT) was worst during fall and best during winter and summer. While there were pockets of exceptional skill during winter (southeast CO) and summer (central NM and northern UT), overall skill scores were not significantly higher than for the CPC operational seasonal forecasts (Figure 7.7).

While the production and issuance of SWcasts ended in 2018, a renewed effort at regional statistical forecasts could capitalize on two decades of additional training data for both predictors and predictands, and improved forecast schemes.

Seasonal forecasts of SWE using GCMs

Kapnick et al. (2018) drew widespread attention with their claim of skillful prediction of regional snowpack (SWE) conditions up to 8 months in advance using a suite of coupled climate models (i.e., GCMs) developed by NOAA GFDL to generate hindcasts for the 1981–2015 period. While they show skill over the western U.S. overall (average correlation of 0.48) and in many sub-regions, the lowest skill (correlation of about 0.30) was found in their Colorado Rockies sub-region, which comprises western Colorado and is the source of about 70% of Upper Basin streamflow. So the relevance of their findings for the Colorado River Basin is more limited than for other regions. Overall, their spatial patterns of skill in predicting snowpack, temperature, precipitation, and storm tracks strongly suggest that they have largely rediscovered the well-known ENSO influence on western U.S. hydroclimate, rather than a truly novel capability of GCMs.

Year 2 predictability during La Niña events

Wolter and Timlin (2011) diagnosed that La Niña events have a much higher propensity for multi-year extension than El Niño events. More importantly, there is a strong tendency for a second-year La Niña to be significantly drier in the Upper Colorado River Basin than the first year. Two of the most severe multi-year droughts since 1950 (mid-1950s and early 2000s) were anchored by such long-lived La Niñas. This tendency was seen again in the two-year La Niña events of 2011–2013 and 2016–2018. Okumura, DiNezio, and Deser (2017) independently confirmed this observation of a drier second year during La Niña. However, this only covers a subset of years, and two-year La Niñas are not guaranteed once a La Niña event sets in.

Implications for the Colorado River Basin

The fundamental challenge inhibiting skillful seasonal climate forecasting in the Upper Basin is the same as that at the start of CPC’s operational forecasts almost 25 years ago: Seasonal forecasting skill across the western U.S.—and in most of the world—is largely predicated on ENSO signals, especially for precipitation, but those ENSO signals are overall weak or cancel out on the scale of the entire Upper Basin, and across the fall–winter–spring seasons when most of the water supply is generated. However, there appears to be enough skill for there to be a benefit using climate forecast model output to slightly tilt or weight the ensemble of CBRFC seasonal streamflow forecasts for the Upper Basin, as was done in work by Baker (2019) (Chapter 8.) For the Lower Basin, seasonal climate forecast skill is generally higher than in the Upper Basin, but still much lower than for weather forecasts.

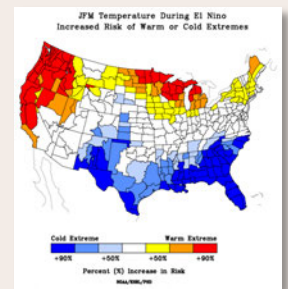
As with sub-seasonal forecasts, perhaps the shortest pathway to “improvement” is for forecast users to judiciously and selectively use seasonal climate forecasts, consulting them only during those seasons, and during those ENSO states (i.e., moderate to strong El Niño and La Niña events) in which more predictability and skill is seen (Figure 7.7 and Table 7.4). A potentially helpful information source in this regard is the NOAA PSD [ENSO climate risk tool](https://www.esrl.noaa.gov/psd/enso/climaterisks/) that shows which climate divisions have significantly increased or decreased risk of seasonal wet and dry extremes (>80th percentile) during moderate to strong ENSO events. During some strong ENSO events, the CBRFC has used ENSO information to adjust streamflow forecasts in the Lower Basin through trace-weighting (see Chapter 8).

7.6 Challenges and opportunities

While there are still many challenges being tackled by the weather forecasting research community to obtain greater understanding and predictive skill, the level of performance and skill is already relatively high, and progressing well. Thus, from the perspective of water supply forecasting and management, the most pressing challenges and most compelling opportunities are at sub-seasonal and seasonal timescales. In the Colorado River Basin, and the Upper Basin especially, the limited skill of sub-seasonal and seasonal forecasts for precipitation and even temperature constrains usability.

There is no single pathway toward improvement in the skill and usability of climate forecasts for the basin. There are, though, broad families of ongoing activities that in combination can lead to such improvement. It is probably neither feasible nor desirable to coordinate all of these activities, since many of them connect with efforts at broader scales; what is important is

Risk of Seasonal Climate Extremes in the U.S. Related to ENSO



Link:

<https://www.esrl.noaa.gov/psd/enso/climaterisks/>

that researchers, funders, and stakeholders are at least made aware of the suite of activities, for example, through the Western States Water Council-California Department of Water Resources workshop series. And, given the history and current state of climate forecasting, no one should expect easy wins producing large gains in skill or usability; incremental improvement is the likeliest outcome of any effort.

Challenge

Limitations in our understanding of the connections between atmospheric and oceanic circulation patterns and processes, and Colorado River Basin precipitation variability in space and time, constrain the skill of climate forecast models in forecasting conditions for the basin.

Opportunities

- Support further research into these climate system dynamics to identify key patterns and variables.
- Support further research into better representing those key patterns and variables in dynamical climate forecast models and statistical forecast tools.

Challenge

The CBRFC and other streamflow forecasting units may not be able to capitalize on the skill that does exist in sub-seasonal and seasonal climate forecasts for the basin.

Opportunities

- Support ongoing CBRFC efforts to pilot the inclusion of sub-seasonal and seasonal forecasts in their forecast system (see Chapter 8).
- Support further research into post-processing of CBRFC forecasts to generate climate-forecast-informed, use-specific streamflow forecasts (see Chapter 8).

Challenge

The limited skill and probabilistic nature of climate forecasts may not mesh well with decision frameworks so water managers are unable to extract value from the forecast information.

Opportunities

- Continue to support engagement between water managers and CPC and other climate forecasters to facilitate shared understanding of decision needs and forecast capabilities.
- Study decision making by users and sectors that make better use of climate forecasts (e.g., crop futures traders), to assess transferability of tools and practices.
- Develop decision support tools that bridge climate forecasts to the water resource decision space.

Challenge

The skill of climate forecasts is highly variable over both space and time, complicating the consistent use of forecasts.

Opportunities

- Selectively consult forecasts during those seasons when they have shown the most skill for the basin.
- Support research to identify “forecasts of opportunity” specific to the basin, i.e., conditions of the ocean, atmosphere, and land surface during which forecasts are more likely to have skill and impact.



Chapter 8

Streamflow Forecasting

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Key points

- Streamflow forecasts from the CBRFC are widely used by water managers in the basin and are critical inputs for Reclamation's operational models, including seasonal forecasts for use in 24MS and MTOM.
- Streamflow predictability at seasonal timescales in the Colorado River Basin arises primarily from the initial watershed moisture conditions, i.e., snowpack and soil moisture.
- While using different methods, the CBRFC and NRCS operational forecasts both effectively capitalize on this predictability, with relatively high skill for forecasts issued in late winter and spring for the coming runoff season.
- To improve streamflow forecasts within the current frameworks there are two main pathways: 1) improve estimates of initial watershed moisture conditions, and 2) improve basin-scale weather and climate forecasts and how they are used in streamflow forecasts.
- Improvements in quantifying watershed conditions can come through better meteorological analyses, more in situ observations of snowpack and soil moisture, increased use of remotely sensed observations, advances in calibration strategies, and advances in data assimilation techniques.
- Improvements in sub-seasonal and seasonal climate forecasts are being actively pursued by national modeling centers and the broader research community; targeted post-processing of climate forecasts can better leverage their current skill to inform seasonal streamflow forecasts.
- Skill in streamflow forecasts for year 2 and beyond is entirely dependent on skill in decadal climate forecasts, which exists to some degree for temperature but not for precipitation.
- Alternative forecast frameworks in which tasks are fully automated permit the use of a greater range of advanced methods and data. These frameworks have not yet been shown, however, to outperform the current operational forecasts.
- Many potential forecast improvement elements have been demonstrated in a research context; systematic testing to benchmark and combine multiple elements could add up to significant overall improvements in operational forecasts.

8.1 Introduction

Operational streamflow forecasting provides invaluable information regarding the expected quantity and timing of streamflow throughout both managed and unmanaged river systems, supporting decision making for a myriad of stakeholder needs. In the western U.S., these include water allocation for agriculture and municipal and industrial supply, flood control,

hydropower, recreation, navigation, and instream environmental uses. The time scale of forecasts supporting operations and management decisions spans hours to years, depending on each managing entity's system capacity and purposes, and the hydrometeorological variability of the streamflow source. In flashy, small catchments where intense convective rainfall can drive flash floods, operational hours-to-days forecasts are common, whereas for the largest reservoirs in the U.S., such as Lake Powell, forecasts extending to 2-5 years are routinely used.

In the Colorado River Basin, the operational streamflow forecasts used by Reclamation and many other basin stakeholders are produced by the NOAA NWS Colorado Basin River Forecast Center (CBRFC). CBRFC forecasts support the flood watch and warning programs of the NWS Weather Forecast Offices (WFOs) and emergency and water management by local and state agencies, tribes, water districts, and Reclamation, which depends on the forecasts to manage the basin's primary reservoirs to meet daily, seasonal, and long-range operating criteria.

This chapter focuses mainly on forecast techniques and models that are relevant to Reclamation operations and planning activities at seasonal and longer time scales, although the same techniques and models are also used for short-range (0-10 day) prediction. Monthly to seasonal ensemble forecasts provide critical input to Reclamation's 24-Month Study (24MS) and Mid-term Probabilistic Operations Model (MTOM), which are used to generate system operations projections up to 5 years out, informing decisions that affect water allocations for stakeholders throughout the seven basin states. As described in Chapter 3, major operational decisions such as the annual release from Lake Powell to Lake Mead depend on storage projections derived using the monthly-to-interannual (mid-range) CBRFC ensemble forecasts. This release, in turn, impacts the operational decisions of stakeholders who must ensure cost-effective and reliable water supplies for their own management domain, hence the forecast impacts cascade through multiple linked levels of decision making.

The CBRFC produces peak-flow, short-range, seasonal, and longer forecast products. The short-range and peak-flow forecasts directly influence daily operations at Reclamation and other reservoir managers, particularly during high-impact weather events (e.g., flood risk) and during snowmelt periods in the spring. In some cases, the short-range forecast can directly determine a reservoir release, whereas in other cases, it may form one of multiple informational inputs that are used more qualitatively to determine a release schedule. The operational watershed models, described in Chapter 6, are initialized each day to generate deterministic, or single value, short-range forecasts for nearly 600 points across the basin.

In addition to the CBRFC, the Natural Resource Conservation Service (NRCS) National Water and Climate Center also produces seasonal water supply forecasts (WSFs) for stakeholders in the basin, but using different methods, as described later. The working relationship of the NRCS forecasts to the CBRFC forecasts has changed over the last few decades (Pagano et al. 2014) as the practice of ensemble forecasting has expanded, but the NRCS forecasts are still widely used to inform water management in the basin. Across the basin, stakeholders consult CBRFC seasonal forecasts, or NRCS seasonal forecasts, or both (Lukas et al. 2016).

This chapter describes the state of the practice for the basin, and what is known about seasonal and spatial variations in predictability and the most promising opportunities for improvement. There is a great deal of literature that documents this topic, and a balance is drawn here between including relevant information about forecast use already documented in sources such as Raff et al. (2013), Mantua et al. (2008), or the recent draft interagency report of the Forecast and Reservoir Operation Modeling Uncertainty Scoping team (Reclamation and Colorado Basin River Forecast Center in preparation), and not re-stating available material. This report covers both short-range and mid-range (seasonal and longer) forecasting approaches because both are critical to the management of reservoirs and water resources in the basin, and the same models are used for both ranges.

8.2 Overview of streamflow forecasting approaches

To understand why different approaches to streamflow forecasting produce more skillful forecasts, and the rationale and suitability of potential pathways for improving forecasts, it is important to understand real-world sources of predictability. This can help gauge whether and where potential improvements may have merit, and how much benefit to expect from them.

Sources of predictability and predictability attribution studies

Streamflow fluctuations are driven both by runoff discharging from water already stored within the watershed—soil moisture, groundwater, snowpack, and the channel network itself—and by meteorological processes (i.e., precipitation and evapotranspiration) in the watershed. Streamflow forecasts are thus ideally driven by two major inputs: 1) the watershed's initial moisture conditions, and 2) forecasts of future weather and climate for the watershed. In practice, in snowmelt-dominated basins in the western U.S. such as the Colorado River Basin, seasonal streamflow prediction skill comes almost entirely from initial moisture conditions, with the level of skill varying by season, from low in the late summer and fall to very high in the spring. Additional skill attributable to weather and climate

forecasts is relatively low at present, and only weather forecasts out to 5–10 days are currently incorporated into CBRFC forecasts (see Chapter 7 and Wood and Schaake 2008; Wood et al. 2016).

The highest predictability at seasonal scales is associated with accumulated winter snow, and to a lesser extent, soil moisture anomalies. The processes through which snowmelt raises soil moisture, generates runoff, and routes runoff through a stream network to produce streamflow is relatively slow, providing useful forecast accuracy at lead times of up to six months (Harrison and Bales 2015; Wood, Kumar, and Lettenmaier 2005). The lowest seasonal streamflow predictability is for forecasts issued after the snowmelt period and preceding significant snowpack accumulations (i.e., from late summer into fall), such that the initial watershed moisture conditions provide little contribution to future flows relative to future weather and climate inputs.

Why is predictability relevant? Operational centers are confronted with a broad variety of potential research and researchers describing upgrades to improve forecasts, yet these may have limited potential for improving any given forecast at important times of year or locations. Upgrading a snow analysis may be a more effective pathway to improved streamflow forecasts for some locations, rather than improving climate forecasts from two weeks to a year in the future, while the reverse may be true in other locations.

Types of streamflow forecasting approaches

Forecasting approaches can be distinguished by several characteristics. These characteristics are discussed below to help provide context on how the current operational forecasts for the Colorado River Basin fit into the overall forecasting landscape. The forecasts to which basin stakeholders have been exposed in recent decades are largely of one type and tradition, yet across the operational centers of the globe there is significant variation in how the same challenges are addressed and in the datasets that are available. It is possible that the range of techniques worth considering may be broader than the perspective available in any one part of the U.S. alone.

Dynamical, statistical, and hybrid methods

Seasonal streamflow forecasting methods are often categorized as dynamical, statistical, hybrid, or a combination. Such approaches span different degrees of complexity and information requirements.

Dynamical methods for seasonal hydrologic forecasting use hydrologic models, ranging from more conceptual models to more physically explicit and process-oriented models to represent hydrologic processes and states in the past, near-term, and into the future (Chapter 6). Model-based seasonal forecasts take a current estimate of watershed conditions and evolve it into the future using either historical observed weather conditions

as proxies for the (unknown) future weather and climate conditions, or inputs derived from seasonal climate forecasts (Wood, Kumar, and Lettenmaier 2005; Beckers et al. 2016). Dynamical methods permit ensemble streamflow prediction, or ESP (Day 1985), as described below.

In contrast, statistical methods rely on statistical relationships (e.g., linear regression) between previous years' observations of seasonal streamflow volumes and several predictors. These predictors include in situ watershed observations, such as NRCS's snow telemetry (SNOTEL) snow water equivalent (SWE) data, and in some cases indicators of large-scale climate patterns such as ENSO. Several statistical approaches can be found in the literature, encompassing different degrees of complexity (Garen 1992; Piechota et al. 1998; Grantz et al. 2005; Tootle et al. 2007; Pagano et al. 2009; Wang, Robertson, and Chiew 2009; Moradkhani and Meier 2010).

Hybrid methods strive to combine the strengths from both dynamical and statistical techniques. For instance, uncertainties in dynamical predictions indicate that dynamical forecasts can benefit from statistical post-processing (Wood and Schaake 2008; Wood, Arumugam, and Mendoza 2018). One line of research has examined the potential benefits of using simulated watershed state variables—either from hydrologic or land surface models—as predictors for statistical models (Rosenberg, Wood, and Steinemann 2011; Robertson, Pokhrel, and Wang 2013). Another popular technique consists of incorporating climate information within ensemble streamflow prediction frameworks (Werner et al. 2005; Wood and Lettenmaier 2006; Luo and Wood 2008; Gobena and Gan 2010; Yuan et al. 2013). Finally, the combination of outputs from different models has also been shown to benefit seasonal hydroclimatic forecasting (Hagedorn, Doblas-Reyes, and Palmer 2005; Najafi and Moradkhani 2015; Mendoza et al. 2017).

Statistical streamflow forecasting has been, for most of the last century, the standard approach, but the use of dynamical methods and ESP has been on the rise (Cloke and Pappenberger 2009; Pagano et al. 2014). Dynamical and ESP-based methods are motivated in part by concerns that regression-based approaches may be unsuitable in the face of non-stationarities associated with climate change and variability (Cayan et al. 2001; Pagano and Garen 2005; Hamlet et al. 2005; Mote et al. 2005; Beckers et al. 2016). Incorporating physically consistent relationships may help better assess hydrologic responses in novel climate situations, as opposed to the fixed, historically trained relationships of statistical methods.

A rapidly emerging perspective is that inaccurate representation of model bounds (i.e., physics) in hydrological models is unavoidable, and machine-learning models have the potential to identify and represent hydroclimate relationships with more fidelity than some process-oriented models (Best

et al. 2015; Nearing et al. 2018). Like traditional statistical models, machine-learning models are trained on observed datasets, and do not include any explicit representation of physical processes such as infiltration, soil moisture storage, evaporation, etc. But machine-learning algorithms (e.g., neural networks) have much greater flexibility to capture non-linearities in the input data and identify relationships in the data that impart predictive skill (Yaseen et al. 2015; Shen 2018). NRCS is actively pursuing the incorporation of machine-learning methods into their seasonal streamflow forecasting approach; Fleming and Goodbody (2019) showed that a multi-model machine-learning ensemble outperformed the current NRCS statistical forecasting approach in three test watersheds, including the Gila River.

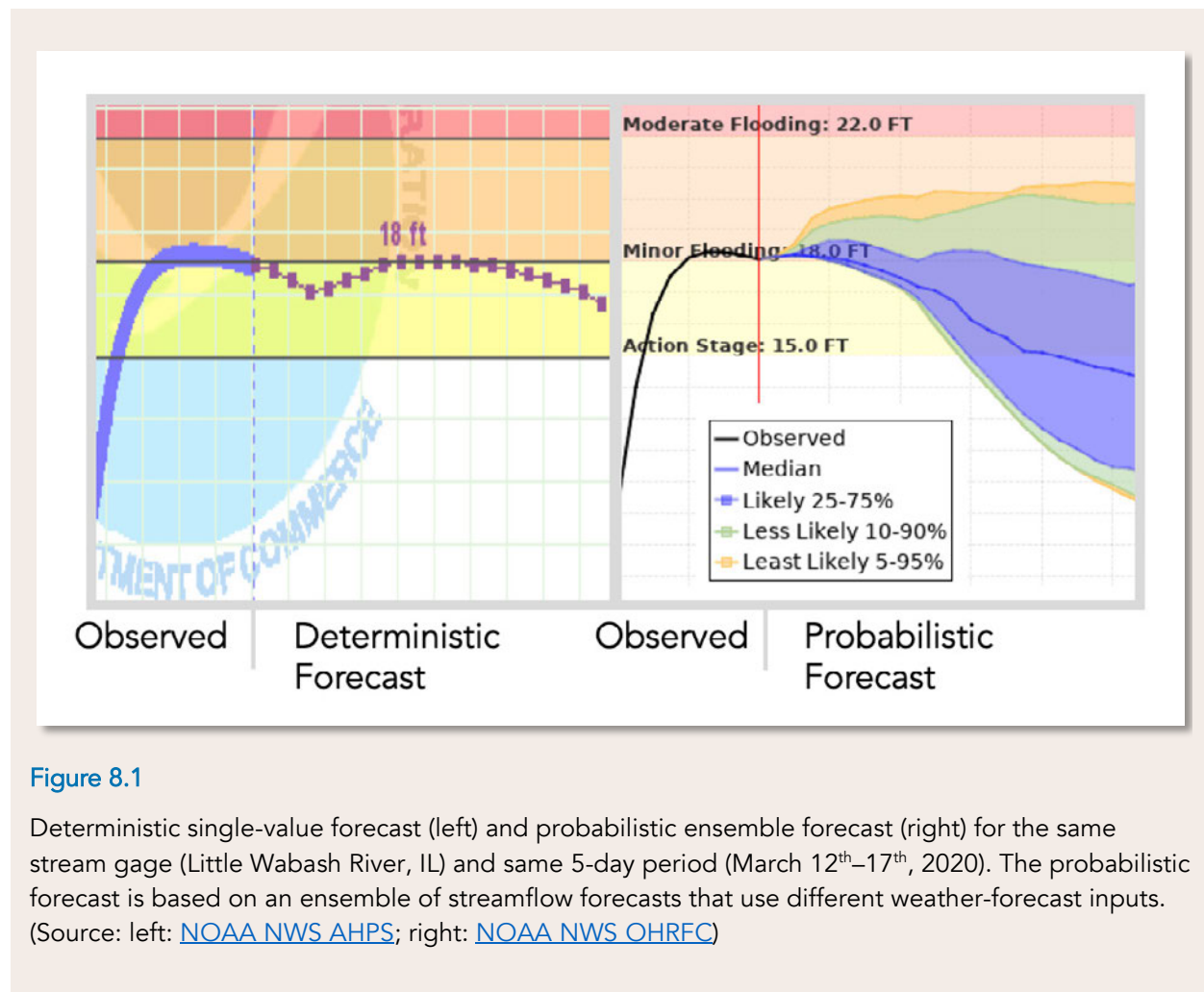
Deterministic (single-value) and ensemble (probabilistic) methods

For many applications, dynamical or statistical approaches for streamflow prediction are used to generate deterministic (also called single-value) forecasts. The forecasts are deterministic in the sense that the meteorological inputs and the model's configuration and parameter specification entirely determine the forecast. The forecasts contain a single value at each time-step of the forecast horizon, and if the forecast model were re-run, the outcome would not change—there is no random or stochastic element in the process that would cause a different outcome.

Ensemble streamflow forecasts (e.g., ESP) involve running the model with a collection of variations in one of the factors influencing the forecasts. Typically, this factor is the meteorological forecast input, in which case a number of variations on this input are sampled from the recent historical record, or taken from a weather or climate forecast model that has been run in an ensemble mode, or some combination. Other potential sources of variation to generate a streamflow forecast ensemble include multiple parameter variations, multiple models, multiple configurations of a single model, or multiple meteorological forcing inputs, which lead to multiple initial states for the forecast. A combination of these could be used, with each set of variations attempting to quantify or estimate a source of uncertainty impacting the forecast—e.g., initial condition uncertainty, future weather and climate uncertainty, or model parameter uncertainty. The resulting ensemble forecasts provide a depiction of the uncertainty as represented by the spread of the forecast ensemble values.

The spread of ensemble values can be used to estimate the probabilities of different outcomes; hence an ensemble forecast is also a probabilistic forecast. Yet the reverse is not necessarily true: Probabilistic predictions generated by statistical techniques that yield only a probability distribution must be subjected to an additional procedure (such as sampling) to generate a matching streamflow ensemble. Example forecasts from the two

approaches, deterministic, single value forecasting and probabilistic, ensemble-based forecasting are shown in Figure 8.1.



In the context of seasonal forecasting, including in the Colorado River Basin, deterministic single-value forecasts are rare because it has long been recognized that futures at seasonal and longer timescales are uncertain. Specialized, single-value forecasts can be found for applications requiring a single trace input (e.g., reservoir models that cannot process an ensemble easily).

Uncoupled vs. coupled forecast systems

Most dynamical forecasting systems are *uncoupled*, that is, the land surface or hydrology model is not run as part of a more comprehensive *coupled* Earth system or numerical weather prediction model. However, a coupled system can be used for seasonal and longer prediction of a hydrologic variable. A recent example is described in Kapnick et al. (2018), in which winter SWE predictions in the southwestern U.S., using a coupled climate model forecast initialized in the prior July, were assessed (see Chapter 7).

Forecasting paradigms

Another important characteristic of forecast approaches that is separate from the types of data and model elements applied is the forecasting paradigm. The forecasting paradigm determines what strategies for advancement may be possible. For decades, a traditional *in-the-loop* paradigm for flood forecasting and seasonal model-based streamflow forecasting has been the norm in the U.S. and internationally, but this is changing as a variety of *over-the-loop* systems are being deployed. In-the-loop systems are those in which the system operation depends on the intervention of human forecasters to adjust components, make inputs or trigger workflows. Over-the-loop systems are those in which the system is fully automated, running without need for intervention from a human forecaster, though the forecasters monitor and interpret output. The forecaster can be considered a critical part of the overall system, enabling it to run through its operational loop.

To understand what these paradigms mean in practice, it is helpful to review the elements of a forecast system (Figure 8.2). *Meteorological forcings* are model input sequences that support model implementation and calibration, and that are updated in real-time and used to initialize (to “warm up”) model states for forecasting. *Weather and climate forecasts* are meteorological input sequences derived from numerical weather predictions and other sources, typically extending 3 to 15 days for flood forecasting systems and out to 9 months to a year for seasonal forecasting systems (Chapter 7). *Hydrologic, hydraulic, and water resources models* are the core of the system. But there are other essential supporting elements, the *meteorological forcings and forecast processors* and the *hydrologic post-processor*, as well as the *land data assimilator*, that make critical adjustments to data as it flows into and out of the model, and to the model states, in real-time. These methods almost always must be applied in some fashion to produce high-quality forecasts, and they are handled differently in in-the-loop versus over-the-loop systems.

In-the-loop forecasting

Traditional in-the-loop flood and seasonal forecasting typically involves a semi-manual process of updating calibrated, conceptual, hydrological models that are run on local computing resources. These efforts generate streamflow predictions at river locations—typically gaged—where forecasts are needed by stakeholders and emergency managers. This forecast paradigm, which is the primary source of short-range forecasts and supports mid-range forecasts at the NWS River Forecast Centers (RFCs) such as the CBRFC, requires expert forecasters to make real-time adjustments to elements of the forecast system described above.

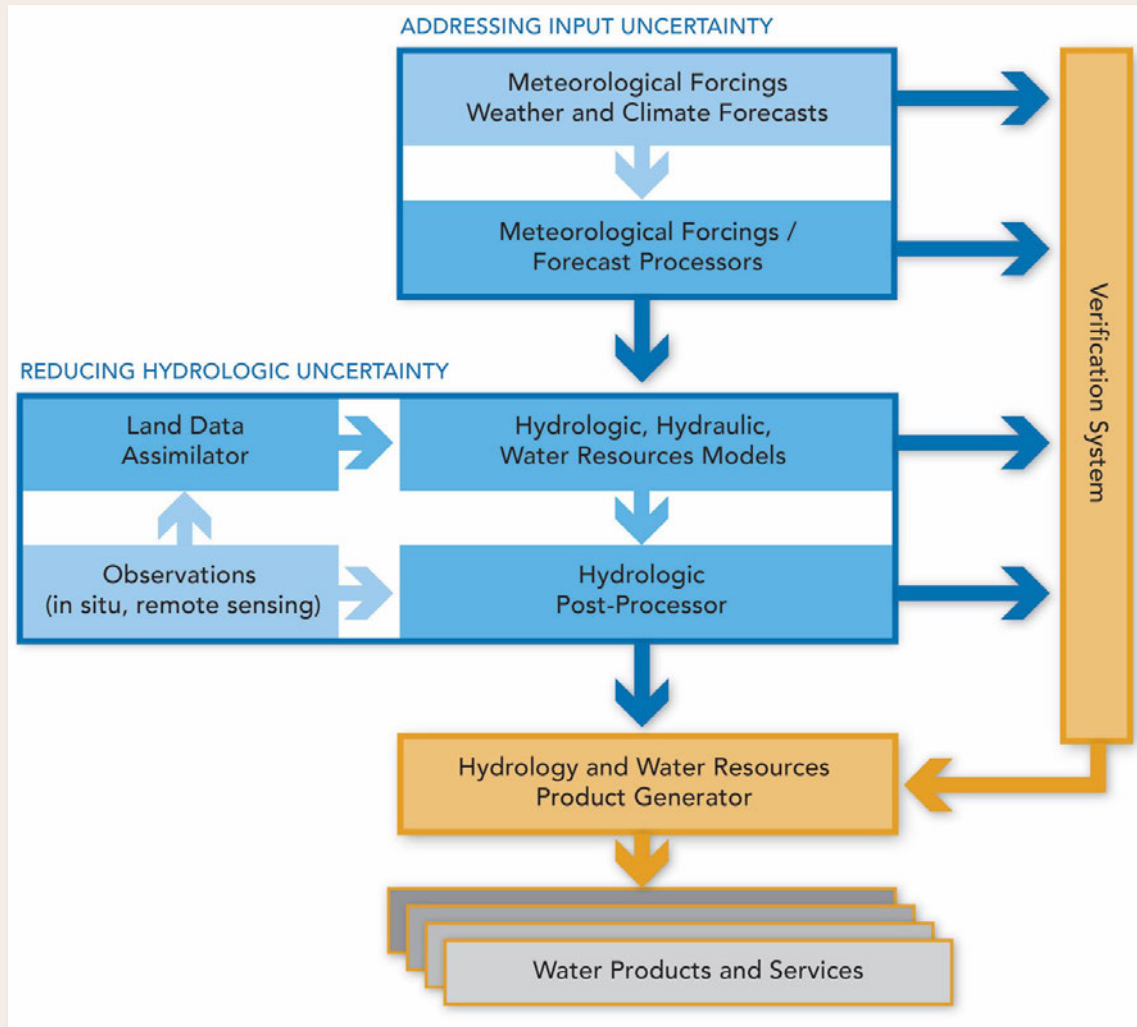


Figure 8.2

Schematic of a model-based streamflow forecasting system. (Source: adapted from NWS online materials: https://www.nws.noaa.gov/oh/hrl/hmsb/hydrologic_ensembles/index.html)

Through this effort, they address the numerous technical and scientific challenges of forecasting, essentially performing pre- and post-processing and data assimilation. Forecaster interventions include the real-time adjustment of hydrologic model inputs, parameters, states, and outputs. This in-the-loop workflow is motivated by the need to overcome—in real time and at times under significant pressure—longstanding challenges in hydrologic forecasting, including ever-present inadequacies in data streams, modeling, system reliability, and interactions with water management systems. It empowers expert forecasters to fix discrepancies between model simulations and forecasts and observed or expected behavior for watersheds with which they may have long experience.

Although this operational practice has changed over time, the semi-manual integration of elements has not. Major changes include upgrading the software for running a forecast, or switching to a new version of a weather forecast model for forecast input, or accessing satellite-based imagery operationally, yet these changes leave the traditional in-the-loop forecast paradigm intact. Notably, in the U.S., including the Colorado River Basin, the in-the-loop paradigm has not yet been outperformed by a different paradigm, and still produces forecasts that inform the management of billions of dollars' worth of water across multiple sectors.

Over-the-loop forecasting

Remarkable scientific and technical advances have been made during the last two decades in many areas supporting hydrologic prediction. Technological upgrades in super-computing, data storage, connectivity, and standardization of data protocols and other forecast system elements provide a foundation for transforming the computational aspects of streamflow prediction. High potential reward research can now be found in several key areas: remote sensing; physically oriented, distributed watershed process modeling and Earth system process modeling; parameter estimation; data assimilation; verification; statistical post-processing; multi-model synthesis; and uncertainty estimation. Numerical weather forecasting in particular has seen steady advances in the skill and abundance of accessible, operational forecasts as well as hindcasts—i.e., datasets of consistent retrospective forecasts (Chapter 7). These advances have spurred the implementation of centralized, automated, forecaster over-the-loop (i.e., no human intervention) systems for short-range and mid-range forecasting in the U.S. and abroad. These over-the-loop systems, such as the National Water Model (NWM; Chapter 6) are now mostly run in parallel to in-the-loop systems and have not replaced them in traditional forecasting for water management.

Over-the-loop systems have made greater inroads in the area of emergency management, such as regional flooding. Forecaster effort is then focused on editing and interpreting automated model output to create products that support decisions in hazard and resource management, and to developing the forecast system.

There are two types of over-the-loop systems—coupled and uncoupled. As described earlier in this chapter, in the uncoupled systems, a land surface or hydrology model is run with meteorological inputs derived from a forcing analysis and weather or climate forecasts, whereas in the coupled systems, runoff from the land surface component of a weather or climate forecast model is routed through a channel routing model to generate streamflow.

Pros and cons of the paradigms

The traditional in-the-loop paradigm results in a highly labor-intensive workflow that limits the ability to use high-resolution datasets and models, apply ensemble techniques, conduct verification and benchmarking for development, and use automated data assimilation approaches that employ reproducible and consistent modeling operations. Changing the forecast paradigm from in-the-loop to over-the-loop therefore sounds attractive, but would require major changes in what a forecaster does and what skill sets they might need to do their jobs. In addition, few effective, fully automated (i.e., over-the-loop) alternatives have been successfully demonstrated in operational contexts for critical parts of the current in-the-loop forecast process, including hydrologic data assimilation, post-processing, and meteorological forecast pre-processing. Furthermore, the traditional approach involves forecasters working hand-in-hand with water system operators to incorporate management operations that affect streamflows. There is as yet no universal solution for doing this in a fully automated way, especially in extreme situations where the managers' and forecasters' decision making may depart from routine practice.

As a result, the forecast outputs of over-the-loop systems such as the NWM, which is relatively uncalibrated, are generally found to be far inferior to in-the-loop systems; where traditional alternatives exist, such as the CBRFC's current models, they are preferred. Some other systems like the uncoupled European Flood Awareness System (EFAS), which has been calibrated, have been more successful and adopted more widely for specific products such as short-range (out to 15-day) forecasts. Another key factor in EFAS's success is that human forecasters oversee and approve EFAS alerts, which are qualitative—providing for operational review of over-the-loop system outputs.

8.3 Short-range (1-10-day) streamflow forecasts

NWS official short-range forecasts

The CBRFC official short-range streamflow forecasts (1-10 days) are single-value predictions for gaged locations, generated each morning, or more frequently during a rapidly evolving flood situation. Forecast locations are coordinated with weather forecast offices, emergency management, or water management agencies to assess risk and inform decisions and actions to mitigate the dangers posed by floods and droughts. Forecasts are made available in a variety of ways, including from the NWS Advanced Hydrologic Prediction Services (AHPS) web page and directly from the CBRFC website.

The Community Hydrologic Prediction System, or CHPS, is an interactive software platform that specifies models and workflows to run traditional

flood forecasts and long-range ESP forecasts. See Chapter 6 for a more detailed description of the CHPS platform and the forecast models used within CHPS, most importantly the Sacramento-Soil Moisture Accounting (Sac-SMA) rainfall-runoff model, and the SNOW-17 snow model.

In the Upper Basin, the forecast models in CHPS typically have a 6-hour time step, while in the Lower Basin, a 1-hour time step is used because of the generally more rapid response of watersheds to precipitation events there. Throughout the basin, the forecasts have a 10-day outlook, with some 15-day forecasts available. Short-range forecasts incorporate forecasted precipitation amounts (QPF) and forecasted temperature (QTF), which is used for precipitation typing and snow modeling (see Chapter 7).

Inputs for the SNOW-17, Sac-SMA, and other forecast models in CHPS, which estimate real-time current watershed conditions, are derived from in situ observations for temperature and precipitation, atmospheric model outputs for freezing level, and remotely sensed estimations (both radar and satellite) for precipitation. Snow-water equivalent, reservoir releases, flow diversions (where known), and streamflow observations are also obtained, and all measured observations are quality-controlled at the beginning of the forecast cycle.

Using workflows specified in CHPS, the models are run beginning with an initial model state (called a warm state) 10 days prior to the forecast date (the date a forecast applies to). A warm state is a model state created during a prior operational cycle in which the model moisture contents have been “spun-up” by simulation over a long enough period (e.g., at least a year) for the states to accurately reflect observed conditions. A cold state, in contrast, has prescribed or default moisture settings that may not match current conditions. Adjustments are then made to model inputs, parameters, and states to obtain streamflow and snow simulations that are consistent with observations over the 10 days leading up to the forecast date. Typically, the most recent day or two is of the most interest to avoid overwriting modifications applied on prior days.

Meteorological forcings

As described in Chapters 5 and 6, the CBRFC forecast model system requires values for temperature and precipitation that are area-averaged for each forecast zone (an elevation band within a catchment) represented in the model. The real-time meteorological forcings are generally produced daily to match the typical forecast production frequency (Figure 8.3), but may be updated more often during a rapidly evolving flood situation.

For the Upper Basin watersheds, which are generally snowmelt-dominated, real-time temperature and precipitation observations—the vast majority from SNOTEL stations—are used to directly produce the areal averages for forecast zones using station weightings determined through model

calibration. The stations that are used have been pre-screened and vetted during the calibration process. Automated procedures identify potentially erroneous station values, which can be then manually corrected by forecasters; manual quality control is also done. Freezing-level data from Rapid Refresh, NOAA’s hourly operational weather reanalysis, is used to run the SNOW-17 model which types the precipitation as rain or snow.

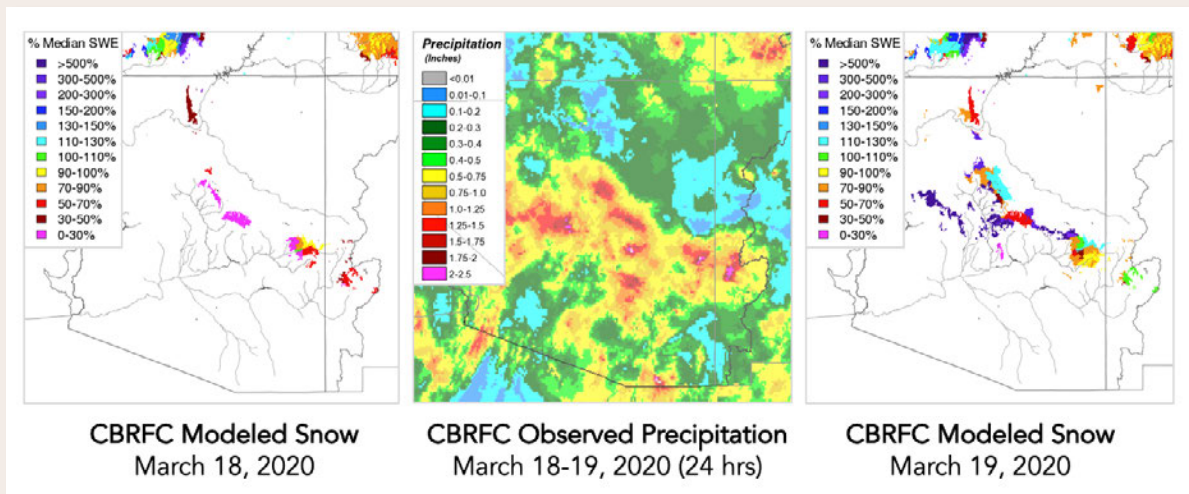


Figure 8.3

A recent CBRFC forecast model sequence illustrating how daily precipitation observations (center) are used in the daily updates of the modeled snow conditions. In the 24 hours ending on the morning of March 19, 2020, there was widespread and often intense precipitation across the Lower Basin, as captured by station observations and radar-based estimates that were integrated into 4-km gridded precipitation values using the Multi-sensor Precipitation Estimate software (MPE; center). The gridded precipitation was used to compute area-averaged precipitation for each forecast zone, which then was used to update the SWE in each forecast zone in the CBRFC snow model (the precipitation was also classified into snow vs. rain using other meteorological data in the snow model). After updating on March 19th, the modeled snow across the Lower Basin (right) showed much higher SWE as a % of average than the previous day (left). (Maps: NOAA CBRFC; precipitation (<https://www.cbrfc.noaa.gov/gmap/gridgeo/gridmap/obgrids.php>); modeled snow (<https://www.cbrfc.noaa.gov/rmap/grid800/index.php>))

For the Lower Basin watersheds, which are generally rainfall-dominated, a denser station coverage is employed, with temperature and precipitation observations from multiple station networks, and then augmented by radar-based precipitation estimates to generate the real-time data (Figure 8.3). The radar data are most useful during the warm season when there is a larger radius of accurate information from the radar, due to radar reflection differences between rain and snow.

The observations from all available stations are used, with no prior screening of stations, to create the highest possible station density. But the station temperature and precipitation values themselves are quality-controlled as in the Upper Basin. As in the Upper Basin, freezing-level data and SNOW-17 are used to type the precipitation into rain and snow. The real-time precipitation observations and radar precipitation estimates are transferred to a 4-km grid using an interpolation algorithm in the Multi-sensor Precipitation Estimate (MPE) software (Figure 8.3), the temperature observations are likewise transferred to a 4-km grid, and then the grid cells within each forecast zone are then averaged to create the MAT and MAP data.

In recent years, the CBRFC has collaborated with NASA to leverage their Moderate Resolution Imaging Spectroradiometer (MODIS) observations to use remotely sensed fractional snow covered area (MODIS Snow Covered Area and Grain, or MODSCAG product) and dust radiative forcing (MODIS Dust Radiative Forcing in Snow, or MODDRFS product; Figure 8.4 and Chapter 5). These estimates provide qualitative corroboration of the model-simulated snow covered area and insight into the potential rapidity of snowmelt due to dust-enhancement, which can then be used to inform real-time forecaster adjustments to the snow model melt factor parameter (Bryant et al. 2013). The watershed moisture conditions resulting from these changes are then used to initialize both the flood forecasts and seasonal water supply forecasts.

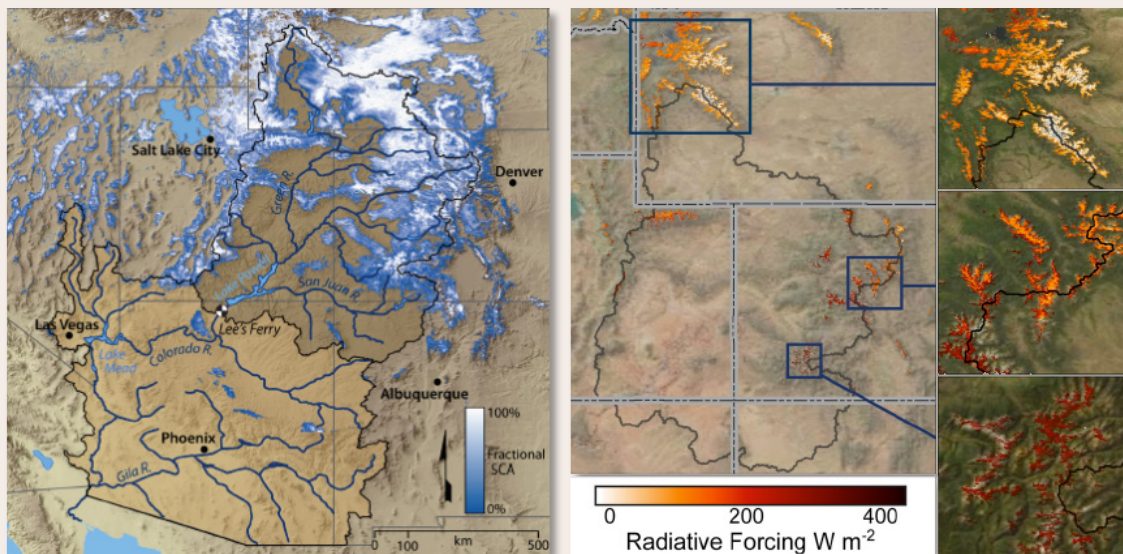


Figure 8.4

NASA JPL remote sensing of snow. Left: MODIS Snow Covered Area and Grain size (MODSCAG), right: MODIS Dust Radiative Forcing in Snow (MODDRFS). (Source: https://arset.gsfc.nasa.gov/sites/default/files/water/Snow/JPL_SnowTraining_w1.pdf)

Hydrologic Ensemble Forecast Service-based forecasts and alternatives

Recent initiatives in the RFCs to roll out ensemble forecasts at the short-range led to development of the Hydrologic Ensemble Forecast Service, or HEFS (Demargne et al. 2014), spearheaded by what is now the NOAA Office of Water Prediction. HEFS was a response to sustained interest in probabilistic river forecasts for short-range flood forecasting and water resources. HEFS uses the models and workflows already used in the traditional forecasting process in CHPS, but adds meteorological ensemble inputs in place of the single-value precipitation and temperature forecasts (QPF and QTF, see Chapter 7), as well as an automated form of streamflow post-processing. It is still largely an in-the-loop workflow that uses the states generated by the official forecast workflow, but the ensemble forecast inputs and post-processing are automated.

Over the last five or six years, HEFS has been steadily deployed for river basins across the U.S., after being run experimentally since 2012 at a few of the RFCs. The goal of HEFS is to produce ensemble short-range streamflow forecasts that seamlessly span lead times from an hour up to several years and that are spatially and temporally consistent, probabilistically calibrated (i.e., unbiased with an accurate spread), and verified. A few forecast centers, such as the California-Nevada River Forecast Center (CNRFC), now present the ensemble forecasts on their web pages in parallel with their official forecasts.

The components of HEFS are shown in Figure 8.5. The most important part of HEFS is the meteorological ensemble forecasts, which are derived via a statistical technique from up to four meteorological forecast inputs. The statistical technique, termed Meteorological Ensemble Forecast Processor, or MEFP, can generate ensembles that seamlessly blend these inputs, with their impact depending on their skill (Wu et al. 2011).

Each RFC uses different models and routines, but almost all of their operations center on the lumped implementation of the Sac-SMA and SNOW-17 models. Like the forecast data from the official forecast process, graphical outputs are also typically available from the forecast centers, so that users can use the data directly in local decision support models.

Around the same period that HEFS was developed, an RFC-led effort created the Met-Model Ensemble Forecast System, or MMEFS (Adams III and Dymond 2018). MMEFS provides short-range (out to 15-day) ensemble forecasts. It differs notably from HEFS in the use of gridded numerical weather prediction ensembles, rather than those generated statistically from NWP ensemble mean forecasts. Both approaches make use of the initial states generated by the in-the-loop official forecast workflow, however.

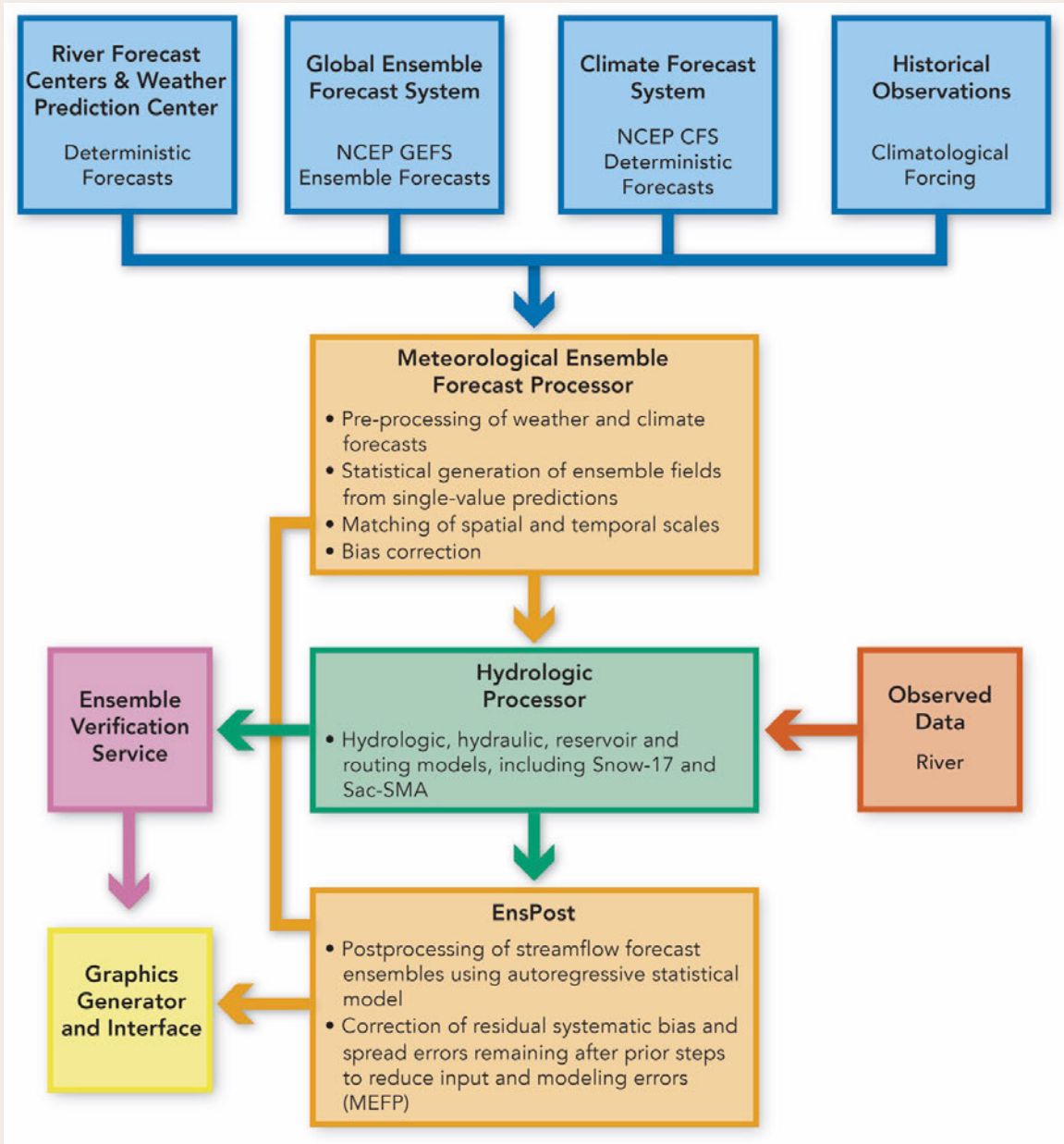


Figure 8.5

Components of the U.S. Hydrologic Ensemble Forecast System. (Source: adapted from Emerton et al. 2016)

8.4 Mid-range (seasonal and longer) streamflow forecasts and water supply forecasts

In the Colorado River Basin and elsewhere, the major methods for operational, seasonal-to-interannual forecasts have been statistical water supply forecasting and dynamical ESP forecasting. Both of these methods are designed to exploit predictability arising from initial watershed moisture conditions (i.e., SWE and soil moisture). The most widely used output derived from these methods is the probabilistic runoff inflow volume forecast (the water supply forecast) for several standard multi-month periods, e.g., April-July or April-September, depending on location. Water supply forecasts have long been expressed in terms of at least three quantiles—10th, 50th (most probable), and 90th—although other quantiles such as the 30th and 70th are also produced for some locations.

Statistical water supply forecasts are generated operationally by the NRCS National Water and Climate Center (NWCC) using principal components regression. The NRCS provides statistical water supply forecasts for approximately 1000 points across the West, overlapping in many locations with RFC forecast points. The CBRFC also develops statistical water supply forecasts (which it calls SWS forecasts) by essentially the same method, but these are only used for internal guidance comparisons with the dynamical ESP forecasts and are not publicly released. Statistical forecasts are described in detail later in this chapter.

Operational dynamical water supply forecasts are produced only by the CBRFC, using ESP methods. For decades, the CBRFC and NRCS coordinated their water supply forecasts for their overlapping forecast points (e.g., Lake Powell inflows) to provide a single official water supply forecast once a month, a process that focused first on reconciling the median forecast and then the 10th and 90th percentile forecasts, so that the two agencies released identical forecasts for those points. In the Colorado River Basin, that explicit coordination ended in 2012, when the CBRFC began providing daily water supply forecast updates using ESP methods. The respective official forecast values from the CBRFC and NRCS for their overlapping forecast points now often differ by up to 10-15% at some locations, particularly for early-season forecasts.

The sub-sections that follow describe in more detail the current practices for developing the CBRFC ESP and official water supply forecasts in the Colorado River Basin, as well as new developments, including a testbed for evaluating mid-range forecasts and their use in reservoir management, and relevant efforts by external groups. The NRCS forecasts are also described in some detail due to their widespread use.

CBRFC operational seasonal forecasts

Ensemble streamflow prediction (ESP) forecasts (daily, mid-December-July)

The ESP approach first simulates the hydrologic state of the watershed during a model spin-up period ending on the forecast start date (Figure 6). The meteorological forcing data for the spin-up period are produced daily by the same procedures as described in the section on short-range forecasts. The initial hydrologic state forms the starting point of an ensemble of forecast simulations that are driven by historical sequences of temperature and precipitation as model inputs (Figure 8.6).

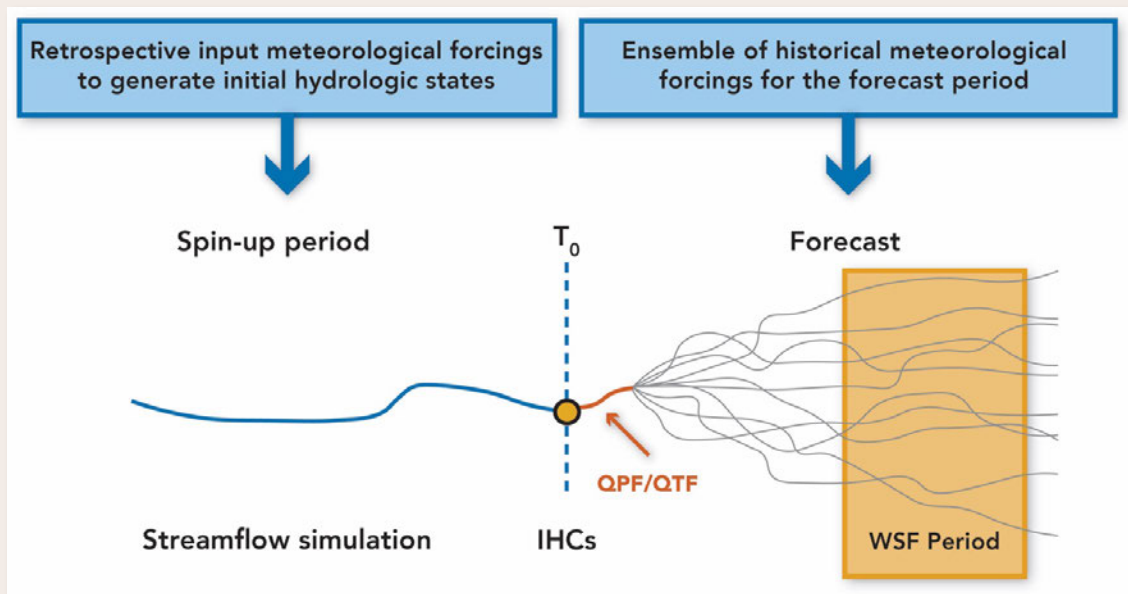


Figure 8.6

Illustration of an ESP forecast with embedded short-range meteorological forecast, and extension into a water supply forecast period for which the runoff volume percentiles are calculated. IHC=initial hydrologic conditions, WSF=water supply forecast, QPF and QTF=quantitative precipitation and temperature forecasts, respectively. (Source: A. Wood)

The start and end dates for historical input sequences for the CBRFC have generally followed the most recent 30-year World Meteorological Organization climate normal period, which is updated every 10 years, hence the most recent normal is 1981–2010. So that their forecast inputs would incorporate the latest information, including recent dry years, in 2016 the CBRFC extended the period of their historical input sequences to 2015, or 35 years (1981–2015). Although the CBRFC uses a 35-year period of record for forecasting, statistics such as percent of average are calculated using the 1981–2010 period. The 30-year climate normal period will be updated after 2020 to the 1991–2020 period; the CBRFC plans to continue adding

years used to generate the ensemble, and will likely use a 40-year period of record (1981–2020) after the climate normal period is updated.

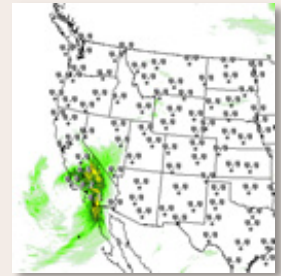
For mid-range forecasts at the CBRFC and other RFCs, the general ESP strategy of using a suite of historical sequences to represent the uncertainty in future climate over the next several months is slightly modified by inserting single-value precipitation and temperature forecasts for the first 5–10 days for QPF and 10 days for QTF (Figure 8.6). This imparts the high skill of short-range weather forecasts to the streamflow forecast, but leaves intact the assumption that the weather beyond 5–10 days is best defined by the historical climatology. Historically, the QPF and QTF were developed by forecasters by merging national gridded predictions from a number of sources, including the Weather Prediction Center and the Weather Forecast Offices, and CHPS then maps these to the watershed model zones.

The CBRFC QPF input source for the first 24 hours of the forecast period is the QPF from the National Blend of Models, and for days 2 through 7 of the forecast period, it is the QPF from the NWS Weather Prediction Center. The forecasters still have the ability to make changes to QPF and QTF before that data gets fed into CHPS, but this should only happen on rare occasions. In such cases, QPF and QTF may be further modified on a model zone-by-zone basis (e.g., the lower, middle, and upper zones of each watershed, see Chapter 6). ESP forecasts both with and without QPF and QTF are produced.

Currently, the ESP workflow is run every day, after the short-range forecast is completed. At key times during the water supply forecasting period, senior forecasters and the forecasters who are assigned to specific river basins (e.g., the Colorado headwaters, the Green River Basin, the San Juan River Basin) review and may adjust model parameters when physically justified to better simulate streamflow. The soil moisture states are adjusted in fall before the snow accumulation season begins, during which soil moisture conditions tend to remain in quasi-stasis until the snowmelt period begins. As the snow melts in the spring, soil moisture conditions that have persisted from the previous fall influence the runoff efficiency, an effect that is thought to make up to a 10% difference in expected runoff volumes (P. Miller, pers. comm.).

The CBRFC produces daily ESP forecasts of both unregulated and regulated streamflows (Chapter 5). Unregulated ESPs represent natural flow in the sense that measured upstream activities (e.g., reservoir operations or measured diversions) are estimated and their impacts on flow are reversed or backed out. In the regulated ESPs, the effects of reservoir operations that are modeled within CHPS as well as known or estimated consumptive uses and water transfers are included in the ESP. CHPS models reservoirs

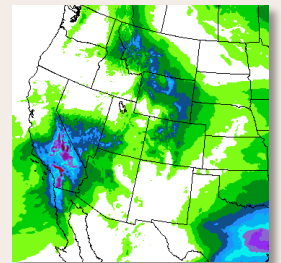
NOAA National Blend of Models QPFs



Link:

https://sats.nws.noaa.gov/~nbm/nbm_graphics

NOAA Weather Prediction Center QPFs



Link:

<https://www.wpc.ncep.noaa.gov/qpf/day1-7.shtml>

with a routine that allows for prescribed releases and fill and spill operations following reservoir rule curves and downstream release constraints and targets. The regulated ESP forecasts are coordinated by forecasters with Reclamation, who provide release guidance for CRSP reservoirs, which also informs the official, regulated water supply forecasts.

The CBRFC produces a range of products from the ESP beyond the summary percentile forecast values (10th, 50th, 90th, etc.). Most notably, the forecast evolution plot tracks the current ESP forecast from early December, once the appropriate adjustments to soil moisture parameters have been completed, along with accumulated forecast period runoff, annotated with thresholds for climatological means and medians (Figure 8.7).

Another product is a comparative cumulative distribution function (CDF) plot, which compares the climatological CDF to the conditional CDF, the conditional CDF being the expected range of water supply forecast outcomes given current watershed conditions.

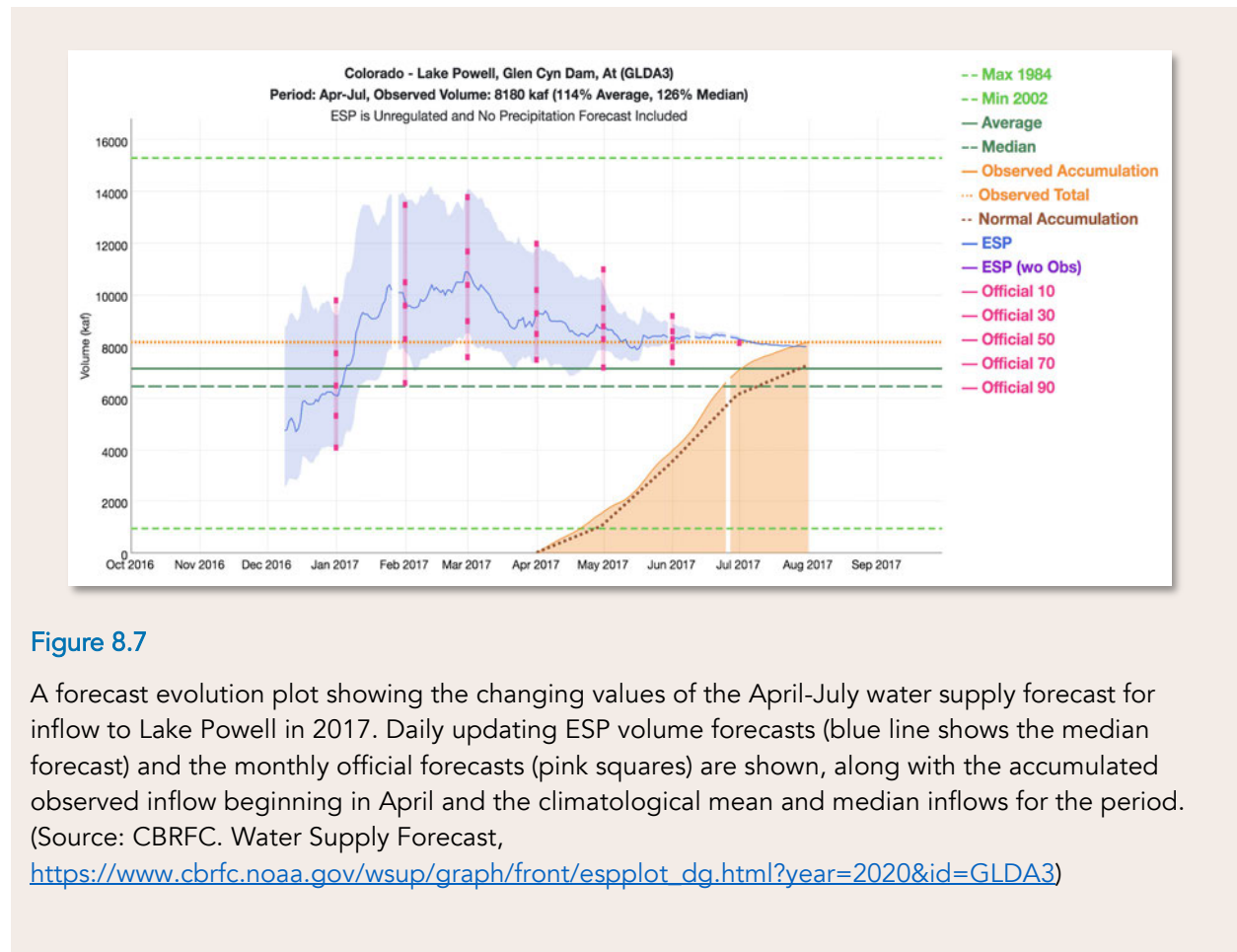


Figure 8.7

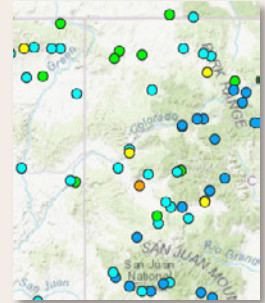
A forecast evolution plot showing the changing values of the April-July water supply forecast for inflow to Lake Powell in 2017. Daily updating ESP volume forecasts (blue line shows the median forecast) and the monthly official forecasts (pink squares) are shown, along with the accumulated observed inflow beginning in April and the climatological mean and median inflows for the period. (Source: CBRFC. Water Supply Forecast, https://www.cbrfc.noaa.gov/wsup/graph/front/espplot_dg.html?year=2020&id=GLDA3)

CBRFC official water supply forecasts (monthly, January-July)

During the water supply forecast season from January through July, the CBRFC produces monthly official seasonal water supply forecasts. While these are current for the 1st of the month, they are not released until several days later, with that lag reflecting the forecasters' consideration of multiple guidance sources for the official forecasts. As noted above, the CBRFC increasingly relies on the daily ESP to set the official forecasts, as can be seen in the very close correspondence between the median ESP and Official 50th percentile forecasts in Figure 8.7. Another source of guidance in the development of the official forecast is statistical water supply forecasts, both the SWS that the CBRFC still produces in-house and the NRCS monthly forecasts described below.

Historically, the skill of the CBRFC ESP and SWS forecasts had been comparable, but more recently the ESP forecasts have shown greater skill at most forecast points. The CBRFC provides a verification page on their [website](#). An example of the Green River at Green River, UT forecast verification, provided in Figure 8.8, shows the ESP forecast is generally more skillful than the SWS forecast. The greater skill of ESP forecasts shown in Figure 8.8 is generally representative of the vast majority of the CBRFC forecast points (P. Miller, pers. comm.).

Historical Water Supply Verification



Link:

<https://www.cbrfc.noaa.gov/arc/verif/verif.php>

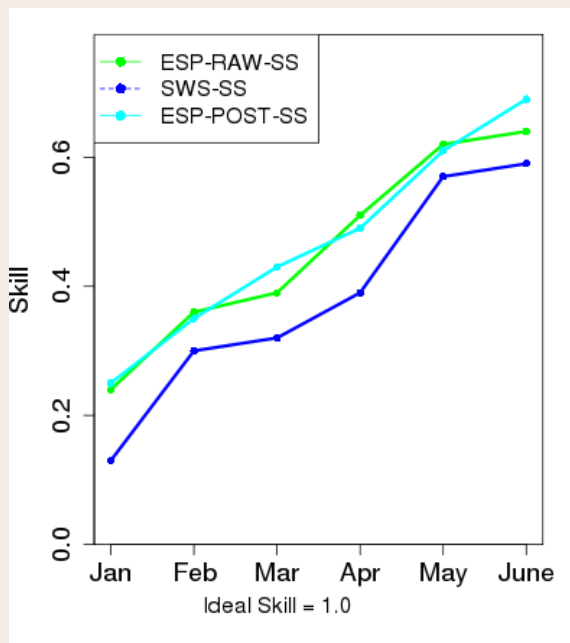


Figure 8.8

Comparison of seasonal (April–July) forecast skill between CBRFC ESP (dynamical) and SWS (statistical) methods at various lead times as indicated on the x-axis for the Green River at Green River, UT forecast point (GRVU1). Skill scores were calculated from reforecasts for the 1981–2010 period. (Source: CBRFC; <https://www.cbrfc.noaa.gov/rmap/wsup/point.php?rfc=cbrfc&id=GRVU1&wyear=2017&mode=reverif&qpf=0&showesp=1&showunapp=0&showoff=1&showobs=1&showmm=1&showhvol=0&mode=reverif>)

The statistical forecasts are trained to be statistically reliable, meaning that they have uncertainty bounds that verify against the observed error, whereas the bounds of the ESP forecasts become increasingly unreliable (“underdispersive”) as the water year progresses toward the annual snow

peak. This is because the single initial condition used in ESP does not reflect the model uncertainty, which has its greatest impact when the contributions to spring runoff are strongly contained within the model snow and soil moisture storages rather than in the future climate, as is the case early in the season. This issue was detailed in Wood and Schaake (2008) along with a post-processing approach to correct for it. The CBRFC evolution plot (Figure 8.7) shows both a daily updated ESP and a periodically updated official forecast. Although the raw SWS is not shown on the plot, a merging between ESP and SWS may be apparent later in the season, as the more statistically reliable and wider SWS bounds extend the official forecast range beyond the narrower ESP bounds.

Applications of CBRFC forecasts in the basin

The daily ESP forecasts serve many water management clients. Utilities such as Denver Water and the Metropolitan Water District of Southern California use them as input for reservoir system models. Most notably, the ESP median trace makes up the most skillful part of the 24-Month Study (24MS) for Reclamation's management of Lakes Mead and Powell. The specific forecast products that are used as inputs into 24MS, depending on lead time and season, are shown in Figure 8.9 and explained in detail in Chapter 3. As noted in the following section describing the Upper Colorado Forecast Testbed, alternatives for various inputs to 24MS are being evaluated. The full ESP ensemble is used in MTOM, which provides an alternative projection (out to 5 years) of Lakes Mead and Powell management.

Conditional ESP input generation approaches

As noted earlier, the primary operational methods for seasonal forecasting do not generally incorporate climate information specific to the forecast period, and instead rely on the initial hydrologic condition signal. For this reason, throughout most of the history of seasonal forecasting, operational predictions were only issued after the start of the snow accumulation period (e.g., starting January 1) due to the initial hydrologic conditions signal provided by SWE and similar information. Yet, a number of studies have shown a benefit from using climate information (Wood and Lettenmaier 2006; Mendoza et al. 2017; Wetterhall and Di Giuseppe 2018). Climate information can come in the form of an expected tendency (e.g., wet and cool) based on historical relationships with the observed climate system state (e.g., El Niño), or from a model-based climate forecast (Chapter 7). As noted previously, the HEFS that is part of CHPS is an important effort toward providing a mechanism for including climate forecasts in seasonal and longer ensembles, which would fill a long-recognized potential gap.

Month Issued	Year 1												Year 2											
	Oct	Nov	Dec	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep
Oct	RFC	RFC	RFC	ESP Oct	ESP Oct	ESP Oct	ESP Oct	ESP Oct	ESP Oct	ESP Oct	ESP Oct	ESP Oct	inter-polate	inter-polate	30-yr Avg	30-yr Avg	30-yr Avg	30-yr Avg	30-yr Avg	30-yr Avg	30-yr Avg	30-yr Avg	30-yr Avg	
Nov		RFC	RFC	RFC	ESP Nov	ESP Nov	ESP Nov	ESP Nov	ESP Nov	ESP Nov	ESP Nov	ESP Nov	inter-polate	inter-polate	30-yr Avg	30-yr Avg	30-yr Avg	30-yr Avg	30-yr Avg	30-yr Avg	30-yr Avg	30-yr Avg	30-yr Avg	
Dec			RFC	RFC	RFC	ESP Dec	ESP Dec	ESP Dec	ESP Dec	ESP Dec	ESP Dec	ESP Dec	inter-polate	inter-polate	30-yr Avg	30-yr Avg	30-yr Avg	30-yr Avg	30-yr Avg	30-yr Avg	30-yr Avg	30-yr Avg	30-yr Avg	
Jan				RFC	RFC	RFC	Official A-J	Official A-J	Official A-J	Official A-J	ESP Jan	ESP Jan	inter-polate	inter-polate	30-yr Avg	30-yr Avg	30-yr Avg	30-yr Avg	30-yr Avg	30-yr Avg	30-yr Avg	30-yr Avg	30-yr Avg	
Feb					RFC	RFC	RFC	Official A-J	Official A-J	Official A-J	ESP Feb	ESP Feb	inter-polate	inter-polate	30-yr Avg	30-yr Avg	30-yr Avg	30-yr Avg	30-yr Avg	30-yr Avg	30-yr Avg	30-yr Avg	30-yr Avg	
Mar						RFC	RFC	RFC	Official A-J	Official A-J	ESP Mar	ESP Mar	inter-polate	inter-polate	30-yr Avg	30-yr Avg	30-yr Avg	30-yr Avg	30-yr Avg	30-yr Avg	30-yr Avg	30-yr Avg	30-yr Avg	
Apr							RFC	RFC	RFC	Official A-J	ESP Apr	ESP Apr	inter-polate	inter-polate	30-yr Avg	30-yr Avg	30-yr Avg	30-yr Avg	30-yr Avg	30-yr Avg	30-yr Avg	30-yr Avg	30-yr Avg	
May								RFC	RFC	RFC	ESP May	ESP May	inter-polate	inter-polate	30-yr Avg	30-yr Avg	30-yr Avg	30-yr Avg	30-yr Avg	30-yr Avg	30-yr Avg	30-yr Avg	30-yr Avg	
Jun									RFC	RFC	RFC	ESP Jun	ESP Jun	ESP Jun	ESP Jun	ESP Jun	ESP Jun	ESP Jun	ESP Jun	ESP Jun	ESP Jun	ESP Jun	ESP Jun	
Jul										RFC	RFC	RFC	ESP Jul	ESP Jul	ESP Jul	ESP Jul	ESP Jul	ESP Jul	ESP Jul	ESP Jul	ESP Jul	ESP Jul	ESP Jul	
Aug											RFC	RFC	RFC	ESP Aug	ESP Aug	ESP Aug	ESP Aug	ESP Aug	ESP Aug	ESP Aug	ESP Aug	ESP Aug	ESP Aug	
Sep												RFC	RFC	RFC	ESP Sep	ESP Sep	ESP Sep	ESP Sep	ESP Sep	ESP Sep	ESP Sep	ESP Sep	ESP Sep	

Figure 8.9

The specific forecast products that go into Reclamation’s 24-Month Study. Greater detail and explanation for this figure is provided in Chapter 3. (Source: Reclamation)

ESP post-processing and trace weighting

Ensemble trace weighting is one of the most common approaches for post-processing ESP forecasts to incorporate a climate signal. Hamlet and Lettenmaier (1999) used the current ENSO index to select ESP traces from ensemble members from years with similar ENSO conditions, while discarding other traces, which improved seasonal streamflow prediction skill for rivers in the Pacific Northwest.

A simple category selection technique was generalized by Werner et al. (2004) to allow a local weighting of ESP members based on similarity to current climate conditions. For instance, in an El Niño year, historical input sequences from El Niño years in the past would have high weight, while those from La Niña years would still be included but with a very low weight. Similarity can be defined by any hydroclimate factor deemed relevant or likely to add skill, though Werner et al. (2004) used climate indices. More recently, Bradley, Habib, and Schwartz (2015) further demonstrated that ESP trace-weighting can improve forecast skill, assuming that informative covariates (i.e., predictors like ENSO state in the Pacific Northwest), are available for the basin of interest (Beckers et al. 2016).

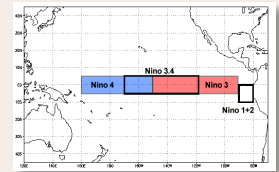
The trace-weighting technique is more straightforward to implement than methods that require the pre-generation of conditional forcings (Wood and Lettenmaier 2006; Verdin et al. 2018; or the MEFP approach). It is important

to recognize, however, that trace-weighting can only reshape the distribution of an ESP forecast within its original distributional bounds (Mendoza et al. 2017). This potentially limits the impact of trace-weighting if the ESP forecasts are biased, in contrast to techniques that are unconstrained in harnessing climate-based predictability.

Several forecast centers have experimented with trace-weighting or post-weighting in the past, in particular using the NOAA Climate Prediction Center's official climate forecasts (Chapter 7) as a conditioning factor, or using popular climate indices, such as Niño 3.4 for ENSO. During several past strong ENSO events, the CBRFC has weighted the historical years for their ensemble streamflow forecasts for Lower Basin forecast points to account for historical ENSO influences on Lower Basin winter and spring precipitation: during an El Niño event, the historical La Niña years (based on Niño 3.4) were removed from the ensemble, with the reverse for La Niña events. The CBRFC would also “nudge” the official forecasts according to this “ENSO ESP” output. However, there has been no formal verification showing that the ENSO ESP is more skillful than the normal ESP that includes all years; the Lower Basin forecast errors in spring 2016 were especially large because the expected influence from the very strong El Niño event that year was not realized (P. Miller, pers. comm.) The CBRFC plans to develop more rigorous verification and a revised method for incorporating ENSO influences into Lower Basin water supply forecasts.

Independent of whether or not trace-weighting is incorporated into official NWS forecast products, users can apply trace-weighting to the ESP forecasts generated by the RFCs. Reclamation is currently investigating whether new climate forecast products from the National Multi-model Ensemble (NMME) may be useful for enhancing the skill of statistical and ESP based forecasts. In the Upper Colorado River Basin, Baker (2019) used an ESP trace weighting scheme—the K-nearest neighbors (K-NN; Gangopadhyay et al. 2009) analog identification technique—to weight traces based on NMME 1-month and 3-month temperature and precipitation forecasts, and also the preceding 3-month average observed streamflow. This analysis was conducted to guide further analyses and modeling within the Colorado River Basin Streamflow Forecast Testbed (see section 8.6). Each predictor used in analog selection were prescribed an importance weight. Weights were calculated separately for four sub-basins (the Gunnison, the Green, the San Juan, and the Colorado mainstem, including the headwaters), and the flows from each were recombined into a new, larger ensemble of Lake Powell unregulated inflow forecasts. Analysis of the runoff season unregulated Lake Powell inflow showed that the 4-basin K-NN method is more accurate, as measured by the root mean squared error (RMSE), than basin-wide K-NN or the standard ESP through all leads (Figure 8.10).

Niño 3.4 Region Equatorial Pacific Sea Surface Temperatures



Link:

<https://www.ncdc.noaa.gov/teleconnections/enso/indicators/sst/>

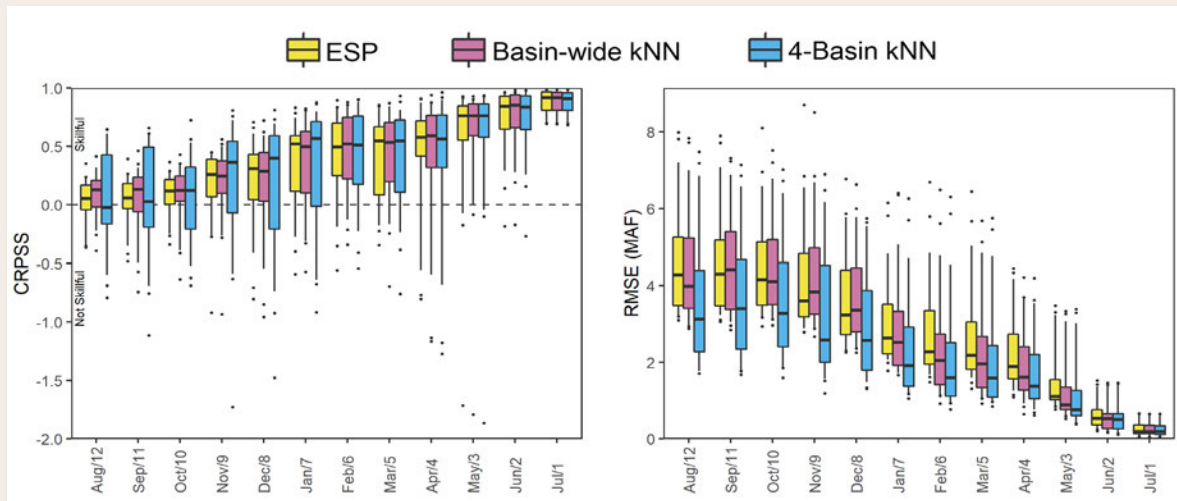


Figure 8.10

Skill scores averaged over a multi-year hindcast for Apr–July Lake Powell unregulated inflow. The streamflow forecasts generated by “standard” ESP, a basin-wide K-NN trace-weighted ESP, and 4-basin K-NN trace-weighted ESP are compared at leads of 12 months (left side of each plot) to 1 month (right side of each plot). The plot on the left shows the Continuous Ranked Probability Skill Score (CRPSS), in which a higher value is better; the plot on the right shows the Root Mean Squared Error (RMSE), in which a lower value is better. (Source: Baker 2019).

A probabilistic skill score, the Continuous Ranked Probability Skill Score (CRPSS) shows median improvements in December–February but a broader spread, with some forecasts ending up worse than ESP. The CRPSS accounts for both mean and spread errors, thus the fact that the K-NN-weighted ESPs tend to be under-dispersive may suffer when assessed by this score. In any case, this work is exploratory and other variations on this approach will need to be investigated. In particular, the use of more skillful, shorter-range weather and climate predictions (1–3 week) and data-driven approaches to predictor selection could be worthwhile.

NRCS operational (statistical) water supply forecasts

As described above, statistical methods are used to produce operational seasonal water supply forecasts (Garen 1992; Pagano, Garen, and Sorooshian 2004; Pagano et al. 2014), and have a history extending at least to the 1940s (Helms, Phillips, and Reich 2008). Based originally on manual snow course observations taken near the first day of each month, these regression-based water supply forecasts were the main motivation for the deployment of the automated SNOTEL network, which currently supplies the SWE and precipitation inputs for the NRCS statistical forecasts. In the early 1990s, NRCS switched to principal components regression (PCR) models from stepwise multiple linear regression to avoid the multi-collinearity problem of interrelated predictors, an issue because SNOTEL

stations in the same basin will depict similar precipitation and SWE anomalies. For daily updating automated (but not official) water supply forecasts, the NRCS also uses a variant on the statistical forecast method called Z-score regression (Pagano et al. 2009).

The most typical streamflow predictors for forecasts in the Colorado River Basin are point-based observations at the SNOTEL stations: water-year-to-date accumulated precipitation, and current snow-water equivalent. In other basins, antecedent streamflow may be used as predictors, as well as ENSO indices. For downstream locations, forecasted flow volumes for the upstream locations are routed downstream, and become key predictors in the regression equations. Recent research by Harpold et al. (2017), funded by NRCS, explored the value of including soil moisture (from in situ observations) as predictors in NRCS equations, finding that they have potential to improve skill. Earlier, Rosenberg, Wood, and Steinemann (2011) showed that the inclusion of modeled estimates of basin SWE and soil moisture in the PCR framework could outperform the use of in situ observations alone. Lehner et al. (2017) showed gains of up to 5% in forecast skill by including temperature predictions from the Climate Prediction Center's North American Multi-Model Ensemble, or NMME, as predictors in the NRCS water supply forecast, a strategy that was then evaluated internally by NRCS. These experimental findings illustrate that the statistical framework provides flexibility to incorporate new types of predictors, whether from observations or models, should they be found to provide increases in forecast skill.

To facilitate forecast equation development, NRCS uses a Microsoft Excel-based tool called VIPER (Garen and Pagano 2007). This tool allows the NRCS to quickly evaluate different predictor combinations with diagnostics on performance and predictor coverage.

Seasonal hydrologic prediction from global forecasting initiatives

Two international operational forecasting centers, the ECMWF and SMHI, are now producing naturalized seasonal hydrologic runoff forecasts for the entire globe (Figure 8.11). Although these efforts are in the initial stages, it is worth mentioning them as possible harbingers of future development. Both systems are based on the ECMWF System 5 seasonal meteorological/climate ensemble forecasts, which are widely regarded as the most skillful in the world. However, to date, their skill has not been specifically evaluated over the Colorado River Basin.

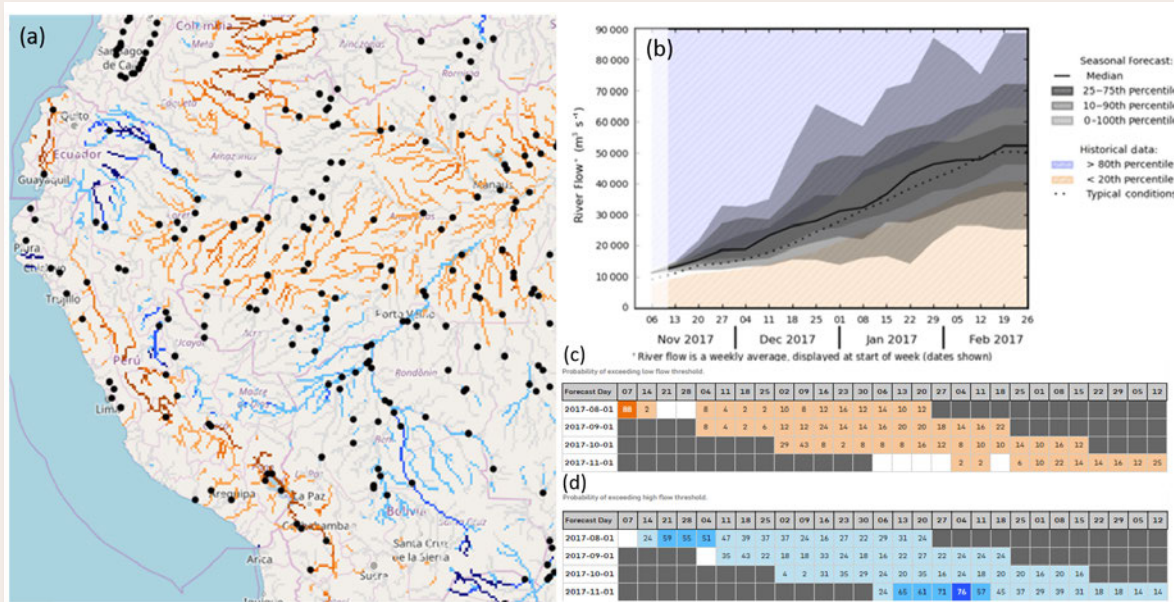


Figure 8.11

GLOFAS based seasonal predictions over western South America. (a) forecast map showing points and anomalies; (b) predicted flow over 4 months with uncertainty bounds; (c-d) probabilities of being significantly below and above normal in future forecast months. (Source: Emerton et al. 2018. © Authors 2018. This work is distributed under the Creative Commons Attribution 4.0 License. Link to license: <https://creativecommons.org/licenses/by/4.0/legalcode>. Link to work: <https://www.geosci-model-dev.net/11/3327/2018/>)

Forecast verification

Verification is the practice of assessing the multi-faceted quality of forecasts in terms of commonly understood metrics of accuracy, reliability and skill. Verification is widely recognized as a critical aspect of the forecast process—essential for identifying and diagnosing weaknesses in the forecast approach, objectively benchmarking new developments against an existing system, and communicating forecast usability to stakeholders (Welles et al. 2007; Demargne et al. 2009; Welles and Sorooshian 2009). It has long been a standard practice in meteorological forecasting centers, which track year-over-year progress on “headline scores” such as the anomaly correlation (AC) of the 500-millibar height field.

In contrast, hydrologic forecasts undergo verification less systematically, and the verification that is performed is rarely made public or published in an organized fashion, with one notable exception described below. There are no comparable, widely used headline scores for hydrologic predictions, either short-range or seasonal. For developers, it can be difficult or impossible to gauge whether a new forecasting approach is better than the existing, official forecasting approach because no consistent (i.e.,

reproducible) operational forecast dataset exists, and metrics for the forecast track record are not readily available. Real-time operations tend to upgrade and evolve steadily, thus the track record of real-time forecasts over time is not consistent with the current system in operations.

Both the NWS RFCs and NRCS have made greater efforts recently to produce and make public verification metrics. Notably, the CBRFC offers more online verification than nearly all other RFCs. For short-range forecasts, the CBRFC shows visual displays of recent forecasts and also of past years' forecasts versus observations, together with a number of statistics for the year. However, long-term verification metrics such as bias, error, correlation, and various indices of reliability are not calculated. For mid-range forecasts, the CBRFC website offers extensive verification plots for each forecast point, accessed via the forecast evolution plot for that point. These verification plots show the skill and error of the actual official seasonal forecasts vs. observations over the past 30 years or so, and also of the retrospective hindcasts (i.e., reforecasts) that are produced using the current forecast procedures. Also available are maps that show the % error of the official seasonal forecasts, by month of issuance, for the years from 2014 to present, as well as a map of the average absolute % error across a longer record of official forecasts (Figure 8.12).

The latest version of the NRCS Interactive Map (5.0) allows users to generate similar maps of forecast errors for the NRCS monthly official seasonal streamflow forecasts, by month of issuance, for any year back to the 1940s, though most forecast points have been active since the 1970s.

8.5 Interannual to decadal hydrologic prediction (year 2 and beyond)

Most operational mid-range predictions focus on lead times of up to one year, but the large storage capacity on the Colorado River drives the need for even longer lead forecasting to support management, as exemplified by Reclamation's 24MS operations model, which requires inflow forecasts extending to two years (Chapter 3). The predictive value of the initial watershed moisture conditions (snowpack and soil moisture)—which is so critical to seasonal streamflow forecasting (i.e., year 1)—is essentially non-existent by the beginning of year 2, let alone further out. Thus, predictive skill for streamflow forecasting at year 2 and beyond can only come from skillful prediction of climate conditions that far out—which falls into the realm of decadal climate prediction (years 2–10).

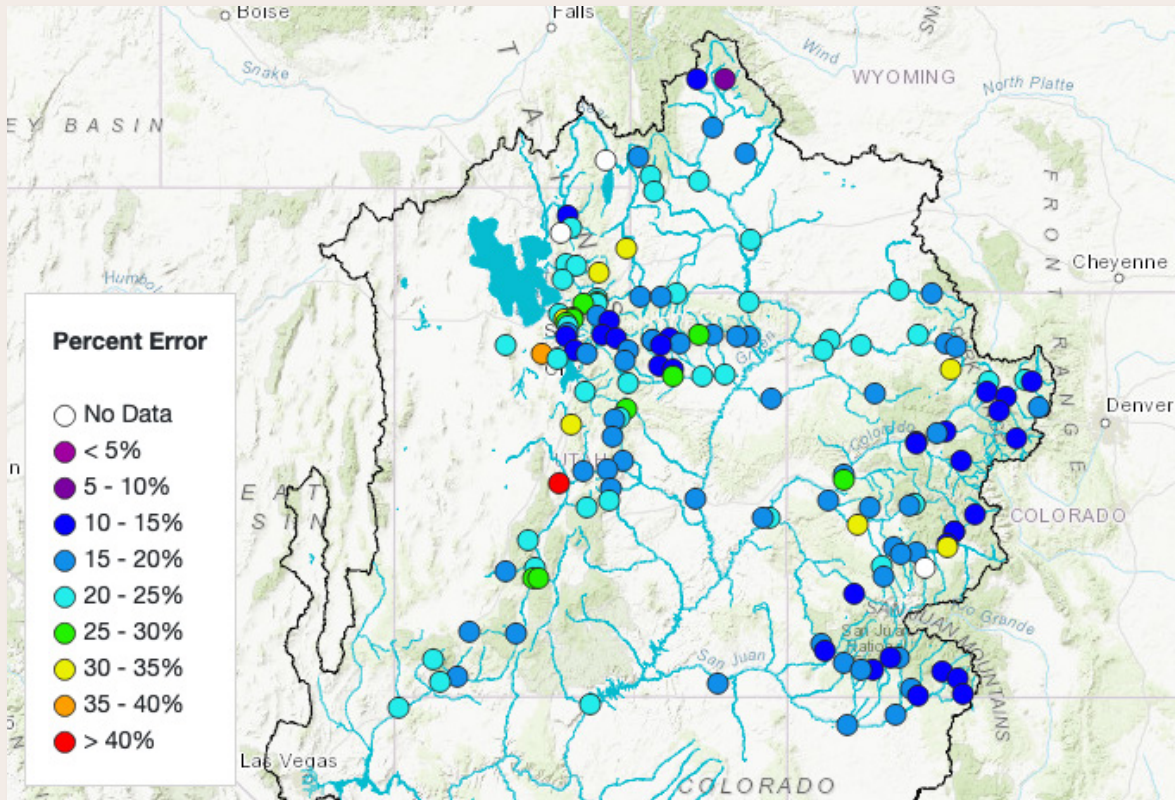


Figure 8.12

Water supply forecast verification map showing the average % error (difference between forecasted and observed streamflow) of the April 1st official forecasts of April-July streamflow for forecast points in the Upper Basin and adjacent portions of the CBRFC forecast domain. Most forecast points have had a forecast error between 10-25%. The period for most gages is 1991-2019. Note that the forecast process has evolved over time, and the historic skill may differ from the current forecast skill. (Source: CBRFC Water Supply Verification 2019); explanation available at <https://www.cbrfc.noaa.gov/arc/verif/verify.year.web.pdf>

Decadal climate prediction is a rapidly evolving field that has recently been boosted by the increasing availability of initialized climate model runs that have been performed to assess whether climate predictability exists at decadal time scales. These decadal predictions use the same climate models (i.e., global climate models; GCMs) and prescribed greenhouse gas forcings as their better-known counterparts, the multi-decadal climate change projections (Chapter 11). However, the decadal predictions have one key difference, which is that the climate model runs are initialized with observed or reanalyzed current conditions, at least to the limited extent that they can be comprehensively estimated, in a manner similar to the initialization of weather forecast models (Chapter 7). For instance, deep ocean variables (which are not included in weather models) cannot be directly observed, although they are known, based on model simulations, to

strongly influence decadal climate. Although experimental, these decadal predictions are being investigated for their potential to provide skillful forecasts for sectoral applications, such as water resources management.

Because of the high computational cost of running the decadal predictions, most performed thus far use only small (10-member) ensembles, which is likely too small to extract a reliable forecast signal given the noise of natural variability that is present at interannual to decadal time scales. An initialized, large ensemble of decadal predictions using NCAR's Community Earth System Model (CESM) was released in 2018 (Yeager et al. 2018). This ensemble includes 40 members. NCAR also has a corresponding uninitialized 40-member large climate projection ensemble from CESM that uses the exact same model configuration and forcings and can be used for an "apples-to-apples" comparison of model performance over the historical period (Kay et al. 2015).

Decadal predictions have shown modest skill for temperature (Yeager et al. 2018), but decadal precipitation forecasts have not been skillful. To a large degree, the skill of decadal predictions of temperature results from warming trends that can be prominent at regional scales (Chapter 2). There is some evidence that low frequency (i.e., decadal and longer) ocean temperature variability, in the form of climate indices such as the PDO and AMO can be linked to southwestern U.S. drought (Chapter 2), but skillful precipitation-related predictions for specific regions and individual years beyond year 1 have not yet been conclusively demonstrated.

Towler, PaiMazumder, and Done (2018) evaluated the use of decadal temperature predictions from the Community Climate System Model, version 4 (CCSM4) for watershed-scale applications. Raw predictions were translated to the local scale by several methods that have been used previously in the seasonal forecasting context. In one, the decadal forecast median temperature anomaly (i.e., the difference from climatology) was added to an observed climate variable, e.g., a time series or climatology of daily temperature observations. In another, the climate forecast was translated into tercile probabilities relative to the model climatology (e.g., below normal, normal, and above normal) and the observed watershed climatology was resampled according to the tercile probabilities or weights. A third method was a hybrid of the first two, in which the resampled forecast is shifted so that its median matched the anomaly forecasts. The study evaluated one decadal forecast (for 2011–2015) in two watersheds, one of which is the South Platte River drainage in Colorado, and found that all of the methods improved the temperature forecast at the local scale (which was for much warmer temperatures than the 1981–2010 climatology), with the anomaly and hybrid methods performing best. Because the study did not evaluate multiple forecasts (e.g., to build a sample of performance statistics), as is typical in forecast method

evaluation studies, the results are not statistically robust. They do, however, align with the general expectations for a temperature forecast, which is that due to the strong observed warming trend, more recent years in the record are warmer than any longer-term climatology, and most initialized climate models capture this trend in sign if not always in magnitude. The same cannot be said to be true of decadal precipitation forecasts, unfortunately.

It may be worthwhile to evaluate not only decadal forecasts from other models, and across a larger forecast events sample, but also against more direct benchmarks such as persistence (i.e., taking the distribution of the most recent 5-10 years as a forecast) or extrapolation of the temperature trend, to assess whether climate model decadal forecasts add marginal skill. If they can capture some of the drivers of decadal variability (such as multi-year ENSO), this additional marginal skill may be possible. In general, decadal climate forecast analyses have not shown significant multi-year skill except in certain windows of opportunity, such as the start of the double El Niño in 1990. The coming years may yield greater opportunities to explore their potential for informing hydrology and water management at regional scales, e.g., as the DecadalMIP runs that are part of the CMIP6 effort become available (Chapter 11).

In addition to the model-based decadal prediction activity described above, there is a small body of literature focused on “year 2” climate and hydrology. Some of this work has been sponsored by Reclamation and has used empirical approaches—i.e., statistically linking observations of climate system variables such as sea surface temperatures or other integrative/lagged observations to regional climate. One example is Lamb (2010), in which sea-surface variability in a region off the east coast of Japan was linked to year 2 hydroclimate in the Colorado River Basin. More recently, Wang et al. (2018) characterized a lagged relationship between Great Salt Lake levels, which integrate climate influences over multiple years, and Upper Basin streamflow. Relationships of this type need to be scrutinized carefully and treated with some skepticism, because it is well known that spurious correlations can arise from the analysis of small samples, and analyzing seasonal variability from the relatively short historical record provides only a small sample. DelSole and Shukla (2009) provide an excellent description of the artificial skill that appears if such analyses are not performed with proper cross-validation, showing that patterns that appear informative can result from random noise. Recent interest in a New Zealand Index that appears to have more mid-range predictability for southwestern U.S. rainfall than the long-used ENSO indices may be another example of such a study in which inadequate predictor screening and cross-validation has been applied, and predictability is overstated. See Chapter 2 for more information about

sources of multi-year hydroclimatic variability and efforts to deploy this information for prediction.

In the context of the 24MS, the lack of convincing predictability for year 2 climate and hydrology in the Upper Basin means that the specification of year 2 inflows (as shown in Figure 8.9) is simply the climatology—i.e., the average of historical inflows. As interest has grown in improving the accuracy of the 24MS projected system conditions, Reclamation has constructed a testbed for evaluating two-year inflow projections, and this testbed is described in the following section.

8.6 The Colorado River Basin Streamflow Forecast Testbed

The generation and advancement of seasonal and longer forecasts, out to lead times of one year, is generally viewed as the operational responsibility of the NWS and the RFCs because any advancement in capability that will serve Reclamation water management must be operationalized within a forecast center or other NOAA office. Although experimental research efforts may provide usable products (e.g., the Westwide Hydrologic Forecast System of Wood and Lettenmaier 2006), water managers are often mandated to use official products from government agency sources. As noted in Chapter 7, NWS has invested in development of improved sub-seasonal and seasonal ensemble climate forecasts, but not in advancing the predictions of year 2 climate. Due to the importance of year 2 conditions for the Colorado River Basin, Reclamation launched an effort in 2016 to assess and compare year 1 and 2 inflow predictions for the basin using the Mid-term Probabilistic Operations Model (MTOM). MTOM simulates operational conditions such as reservoir operations and operating tiers (Chapter 3).

This effort created a testbed, a platform for running MTOM with either the existing operational streamflow forecasts or experimental forecasts, to analyze the impacts on system management. The testbed provides a protocol for evaluating streamflow forecasts and the skill of the resulting hydrologic and operational projections over a 2-year period. Figure 8.13 shows the framework for the Colorado River Basin Streamflow Forecast Testbed. Streamflow forecasts are input and run through MTOM to output operational projections for the basin reservoirs, using a monthly time step to the end of the second water year. Streamflow forecasts are evaluated with metrics that compute the error, skill, spread, and reliability of the Lake Powell annual unregulated inflow. Operational projection metrics assess the errors of MTOM projected pool elevation, storage, outflow, and operating tiers at Lakes Powell and Mead.

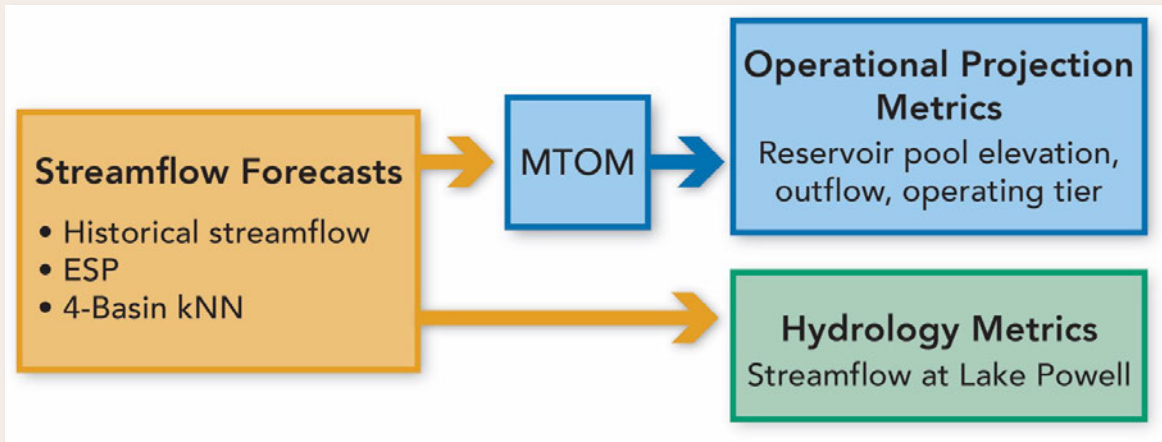


Figure 8.13

Colorado Basin Streamflow Forecast Testbed framework. (Source: adapted from Baker 2019)

The testbed framework utilizes the RiverWare Study Manager and Research Tool (RiverSMART). RiverSMART facilitates the execution of RiverWare models such as MTOM, allowing for easy repetition to explore alternatives, e.g., different hydrology scenarios, demand scenarios, and operating policies. The setup of the testbed in RiverSMART is illustrated in Figure 8.14. A combination of Run Range, DMI (Data Management Interface), and MRM (Multiple Run Management) options allow RiverSMART to simulate forecasts with different run lengths, number of traces, and input format. The scenarios use one model, MTOM, and one ruleset, to simulate reservoir operation according to the 2007 Interim Guidelines. The basin-wide conditions and reservoir operations from each simulation are output to CSV files that are read into R scripts to analyze the streamflow forecasts and operational projections for hydrologic and operational skill.

The testbed has been used to evaluate both deterministic and probabilistic streamflow forecasts. The deterministic “most probable” forecast, which is used in the 24MS, was compared to the median ESP trace for the years 2001–2016. In year 2, both forecasts have large errors, with the Median ESP trace performing slightly better at forecasting Powell unregulated inflow during this time. Three ensemble streamflow forecasts—Climatology, ESP, and 4-Basin K-NN—were compared from 1982–2016. (Figure 8.10 shows a related analysis: the skill of the ESP, 4-basin K-NN, and Basin-wide K-NN ensemble streamflow forecasts over year 1.) To support the testbed analyses, the CBRFC provided 30 years of hindcasted ESPs.

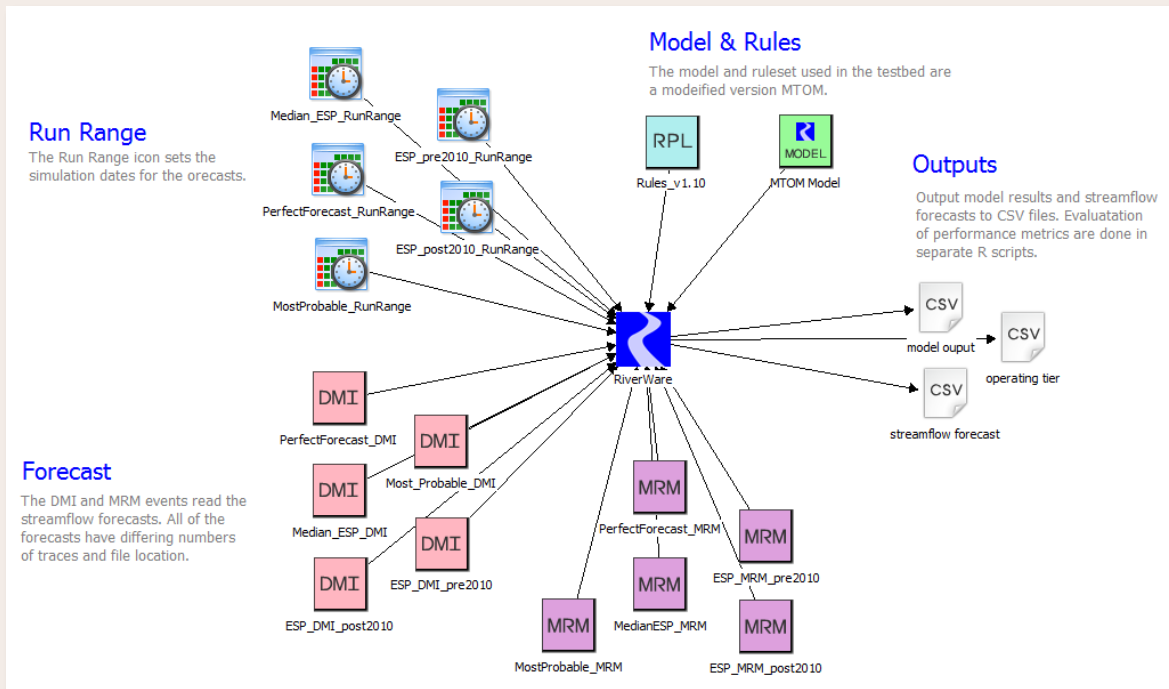


Figure 8.14

Testbed application within RiverSMART. Arrows depict the direction of data flow and process. (Source: Baker 2019)

In year 2, all forecasts have good resolution and reliability, but they lack skill (See Chapter 7 for explanations of these terms). The skill of both the ESP and 4-Basin K-NN forecasts increases above climatology in the fall of the out-year, likely due to the knowledge of antecedent basin conditions such as soil moisture. At shorter leads during the runoff season, ESP and 4-Basin K-NN have poor resolution and reliability. The resulting modeled reservoir operations showed that all forecasts produced large errors in projected pool elevation at Lakes Powell and Mead in year 2. These errors in projected pool elevation decrease with shorter leads, especially by April. These findings are detailed in Baker (2019).

The testbed analyses performed so far have already led to changes in how Reclamation produces operational mid-term projections. Reclamation regularly produces, using MTOM, a 5-year table of future basin conditions and reservoir operations in the Colorado River system. This table was originally produced using the natural flow record (1906–2017) run through CRSS to simulate reservoir operations for the full 5-year table. Based on the results of the testbed analyses, Reclamation now uses the ESP streamflow forecast run through MTOM to project reservoir operations for year 1, and then uses CRSS projections for the subsequent 4 years of the table. See Reclamation’s [webpage](#) for more information on this table.

**Colorado River System
5-Year Projected Future
Conditions**

Link:
<https://www.usbr.gov/lc/region/g4000/riverops/crss-5year-projections.html>

8.7 Challenges and opportunities

Seasonal and longer streamflow forecasts will always contain uncertainty, thus the multi-faceted challenge facing scientists, forecasters and water managers is to identify operationally robust strategies to enhance the skill and reduce the forecast uncertainty, while facilitating further research into improving forecasts. There are three primary pathways toward improving streamflow forecasts. The first is improving predictability arising from initial watershed conditions. The second is improving predictability arising from future climate states. The third is improving the forecasting paradigm to allow for reproducibility, benchmarking, and steady capability and workforce development as the datasets, models and methods evolve. The sub-sections below discuss opportunities in each area.

Meteorological inputs

Model meteorological inputs are critical to model performance. There is currently no high-quality, high-resolution, real-time meteorological analysis that uses all available (and useful) multi-sensor information, and provides 1) consistency to the extent possible between real-time and retrospective forcings; and 2) uncertainty information in the form of ensembles or statistical metrics. Potential opportunities for improvement include continued development of high-resolution datasets of near-surface weather; enhancement of ensemble forcing procedures to incorporate numerical weather prediction and radar and satellite information; and statistical adjustments to improve real-time to retrospective consistency.

Harnessing watershed predictability

Modeling

It is often noted that the current operational model suite for the forecast centers are legacy NWS river forecast system models that were introduced in the 1970s, and that hydrologic modeling has advanced since then in various contexts: process-oriented watershed modeling (e.g., the Distributed Hydrology Soil Vegetation Model), land-surface models (e.g., VIC model), and more recently coupled land surface models that incorporate increasingly complex representations of water and energy balance physics (e.g., Community Land Model). Not surprisingly, there has long been the view that better streamflow forecasts can be obtained by upgrading from legacy models to more complex and physically oriented models.

The National Water Model is the latest NWS-led effort in this direction, following the decade-long effort to introduce the coarser Hydrologic Laboratory-Research Distributed Hydrologic Model in the RFCs for streamflow forecasting. A more recent example is the recently completed partnership between the CBRFC, RTI, and Utah State University under NASA funding to implement an 800m version of HL-RDHM over the Upper

Colorado River Basin for forecasting, and to assimilate MODIS-based snow cover imagery.

Outside of the NWS, there have been, or are, multiple forecasting activities based on different modeling implementations. Notable research efforts have included the aforementioned NOAA-funded, VIC-based, Experimental West-Wide Seasonal Hydrologic Forecasting System at the University of Washington, which ran in real-time over five years, producing ESP and enhanced ESP forecasts and allowing for automated data assimilation. Where calibrated, the VIC-based water supply forecast predictions appeared to have comparable skill to the RFC water supply forecasts. Private-sector efforts also exist, providing short- and mid-range forecasts to reservoir management clients, though these are not well documented.

The modeling advances over the last three decades and their demonstration in forecasting contexts have not altered the reliance of RFC operational practices on the legacy models. There is a clear scientific rationale for enhancing the physics of the legacy models in many forecast cases: for instance, where key runoff generation processes are missing from the models, or where the spatially lumped models cannot represent watershed process heterogeneity sufficiently to represent streamflow dynamics adequately. Examples of the former are when parts of watersheds have burned, which would require different forest cover depictions; or where soil cracking, surface ponding or frozen-ground effects are important. An example of the latter is where the differential timing of snow accumulation and melt in a watershed needs to account for myriad spatially variable factors including elevation, aspect and canopy coverage.

Yet implementing modeling advances faces major hurdles for operational flow prediction in both the current in-the-loop forecast paradigm and a potential over-the-loop workflow. The manual forecaster practice requires relatively low-dimensional (i.e., simpler) models in which model states can be interactively adjusted, which limits the complexity of the modeling structure and physics. It would be impossible for a forecast expert to adjust model states in a high-dimensional model, especially in real-time. And some of the manual adjustments, especially in real-time flooding situations, are critical for incorporating timely updates of management effects such as spillway releases. The models also must run relatively fast to be supportable on current forecast center computational infrastructure—which does not include supercomputing. Also, significantly, the models must be amenable to calibration, yielding high-quality streamflow simulations, which means both that they must be fast, since calibration requires 100s to 1000s of repetitive simulations, and that forecasters have a comprehensive understanding of parameter sensitivities.

The inability, thus far, of agencies and research groups to adequately calibrate more complex models (e.g., the National Water Model) for streamflow simulation has been a major factor blocking their adoption. Complexity that raises the computational demand of forecasting to the extent that various techniques such as data assimilation, hindcasting or mid-range ensemble prediction are infeasible is also a detriment. At present, for instance, the National Water Model runs 30-day lagged-ensemble forecasts, which are not sufficient for many water management applications. In contrast, coarser-resolution systems such as the WorldWideHydro system run full-ensemble forecasts for multiple seasons ahead.

In summary, modeling advances hold potential to improve operational forecasting, but their potential uptake requires several major, challenging scientific and technological upgrades. Simply investing in a new model implementation alone without supporting science and methods (as discussed in Chapter 6) is unlikely to yield improved predictions in the near term. Therefore, the most promising research opportunities include:

- Effective approaches for regional parameter estimation (calibration) in more complex watershed process models to enable model streamflow simulations on a par with the performance of current legacy models. RTI is currently working with the CBRFC on a modeling effort to improve the CBRFC's estimation of consumptive use.
- Effective approaches for automated hydrologic data assimilation, to replace the many manual adjustments made by expert forecasters and enable skillful over-the-loop systems.
- Automated interoperability of water management decisions and river basin modeling systems, to replace the manual incorporation of management effects like releases and diversions.

Some funding toward these aims has been made available in recent years through the NOAA Office of Weather and Air Quality program, but it is almost entirely focused on the high-resolution National Water Model and National Water Center-based forecasting, rather than being more generally targeted toward advancing hydrologic prediction science, regardless of the specific modeling platform.

In addition, research is needed to identify clearly, from a process and information standpoint, where and why additional complexity should be expected to improve a particular streamflow forecast product, whether short- or mid-range. Experience has overwhelmingly shown that the greater complexity in resolution or in process representation does not guarantee improved streamflow simulation and prediction. Often, the reverse is true, thus evidence-based arguments for such advances must be

sharpened, identifying particular forecast applications in particular hydroclimatic settings, to avoid prolonging unproductive model development initiatives.

Improving watershed observations

There is little question that more extensive monitoring of watershed conditions, either by direct or remote measurements, would benefit hydrologic forecasting. The benefits can arise in two ways: 1) improving real-time analyses that provide the initial conditions for forecasts, which matter most when those conditions provide most of the forecast signal, such as in late spring; and 2) improving model implementation by helping constrain model parameters and guide structural implementation of those parameters.

In the first case, increased density of real-time measurements of SWE and streamflow can reduce uncertainty about forecast model states in real-time, reducing errors in the forecasts. Increased accuracy in watershed precipitation and temperature analyses that drive forecast models will also improve real-time states and lessen the need for forecaster manual adjustments. Satellite remote sensing of distributed snow cover and dust-related radiative forcing is currently used by the CBRFC as an ancillary source of information to adjust model states, in a semi-quantitative but not automated process. The relatively newer high-resolution Airborne Snow Observatory (ASO) imagery and other fully spatially distributed snow information (Chapter 5) have potential to improve snowmelt runoff forecasts by providing more detailed and comprehensive characterization of the snowpack. This potential is still being explored.

Soil moisture observations are also potentially beneficial, though both in situ and remotely sensed soil moisture observations (Chapter 5) have not been able to supplement, let alone displace, the use of modeled soil moisture by the CBRFC and other operational forecasters. In situ stations are sparse, insufficiently deep, and typically lack long periods of record, and satellite soil moisture imagery is coarse (typically 25-km resolution) and lacks information for more than the top 5 cm of the soil. To date, remotely sensed soil moisture has not been shown to benefit operational streamflow prediction. A number of studies have shown, nonetheless, that the use of soil moisture observations or estimates, where available, can increase forecast skill. For example, Harpold et al. (2017) achieved a 10-20% improvement in statistical water supply forecast prediction using in situ NRCS Soil Climate Analysis Network soil moisture measurements to supplement SWE and precipitation observations, while Rosenberg, Wood, and Steinemann (2011) similarly demonstrated improved statistical water supply forecast predictions using a combination of VIC-based modeled soil moisture and SWE as predictors. As noted earlier, the current RFC practice

of adjusting modeled soil moistures in fall, ahead of the forecasting season, recognizes the influence of soil moisture on spring-summer runoff.

Many of these hydrologic observations (other than soil moisture, due to its limited availability) can be used to help evaluate and improve watershed models, particularly by extending their assessment beyond a focus on streamflow to include more process-specific, distributed variables. Doing so increases the chance that when the model is simulating streamflow, it achieves good results for the right reasons, i.e., because it simulates watershed sub-processes correctly. Evapotranspiration (ET) estimates from satellites, models, and hybrid satellite/model approaches (Chapter 5) can be used to bracket watershed model ET fluxes and improve the calibration of watershed models. It is unclear, however, whether real-time ET estimates would benefit real-time streamflow predictions significantly, since calibrated models typically can estimate ET relatively well from other meteorological forcings.

There are a number of challenges to effectively using watershed observations to improve forecasts, however, and it is common for the immediate benefit of new or expanded observations to be overstated by groups that have a vested interest in their support, development or adoption. One of the primary challenges is that new observations lack a long enough record to incorporate into operational forecast practice. Watershed models are calibrated over multiple years to their meteorological inputs, so, for example, placing a new radar site for measuring precipitation yields a new input analysis that the model is not trained to handle, and cannot be used immediately in prediction. A number of years of operation may be needed before the radar analysis can be merged with longer-term observational analyses to provide a multi-sensor record that a watershed model can be trained to use. Statistical models have similar training requirements; ideally, they are trained on at least 30 years of predictor observations.

The new high-resolution ASO snow data (Chapter 5) appears to be a high-potential-benefit dataset for seasonal streamflow forecasting, although as noted earlier a comprehensive analysis to determine its optimal application and real marginal value has not yet been performed. For example, it is unknown whether ASO SWE estimates early in the season offer more value than the use of modeled snow water equivalent, either in physically based forecast frameworks or in statistical ones. ASO's distributed snapshots of SWE could possibly be combined with long-term, in situ SNOTEL SWE to reconstruct SWE volumes from long-term index stations, achieving better predictions and possibly avoiding the need for additional or frequent ASO flights. To better understand how much predictive skill ASO snowpack information adds relative to conventional seasonal (water supply) streamflow forecasts, and to test whether a limited number of targeted

ASO flights can be used to improve future forecasts in other basins, Reclamation has an ongoing project that focuses on merging high resolution airborne snowpack data with existing long-term hydrometeorological observations to improve water supply forecasting. In another project led by NASA Jet Propulsion Lab and the CBRFC, ASO SWE observations are being compared with modeled SWE data to determine correlations between the two data sets and assess whether the ASO data could have improved past streamflow forecasts for selected basins.

A number of studies over the last 15 years have tried to show the benefits of assimilating snow covered area data from the satellite sensors MODIS and Visible Infrared Imaging Radiometer Suite (VIIRS) into hydrology models to the benefit of forecasting. These studies have generally suggested minor or negligible gains. McGuire et al. (2006) assimilated MODIS snow parameters into VIC and found moderate improvements in ESP forecasts for a number of locations in Idaho, but in general, relatively few studies exist to assess snow covered area assimilation in a mid-range forecasting context. The CBRFC has operationalized the input of MODSCAG data from MODIS to provide real-time information that can aid the forecasters in adjusting model snow covered area (Chapter 5), but has not quantified the impacts of these adjustments on seasonal forecast skill. MODIS imagery is often cloud-obscured in key regions of the West, including the Upper Basin, during times when it would be useful, thus its operational utility can be limited.

By better characterizing watershed conditions and enhancing our ability to model watersheds, new or improved watershed observations will generally provide a positive return on investment. At certain times of year, when initial hydrologic conditions dominate the mid-range forecast signal, improved initial condition estimates will directly translate into improved mid-range predictions. There is always a need to consider the potential benefits of particular siting locations for new in situ observations such as SNOTEL sites, to avoid redundant measurements and to optimally fill measurement gaps. Rosenberg, Wood, and Steinemann (2013) describe the use of VIC modeling to identify optimal placements for new SNOTEL sites in the mid-range water supply forecasting context—locations where SWE is not highly correlated with existing stations. There are still many forecast locations across the western U.S., including the Colorado River Basin, for which additional in situ SWE, precipitation, temperature, soil moisture, and streamflow measurements could reduce uncertainty in mid-range forecasts.

Spatial observation-based analyses of SWE and soil moisture also have great potential to improve the initial conditions for mid-range forecasts, but it is critical to recognize that their optimal value will be difficult to harness without 1) methodological research into how they may be incorporated into a forecast workflow, at the lowest potential cost, and 2)

the development of both real-time and multi-year (retrospective) records that provide a foundation for research and methodological verification.

Hydrologic data assimilation

The current mid-range forecast paradigm relies on forecaster effort to adjust model states to be consistent with streamflow observations. To open the door for adoption of more complex models, multi-faceted ensemble approaches, leveraging supercomputing, and other advancements in streamflow forecasting, the research and operational communities must develop effective automated hydrologic data assimilation methods that can be applied across regional domains. This transition from in-the-loop to over-the-loop paradigms took place in the meteorological forecasting community several decades ago, but is only beginning to take root in the hydrologic forecasting community today.

The literature is full of small-scale, limited period, case study examples in which hydrologic data assimilation has been shown to be beneficial. Liu et al. (2012) provide a review of hydrologic data assimilation theory and applications, noting that “Despite the overwhelming research into hydrologic data assimilation, only a few studies...formulated data assimilation in an operational setting and attempted to evaluate the performance gain from data assimilation in a forecast mode” and observed that “the application of advanced DA techniques for improving hydrologic forecasts by operational agencies is even rarer...”. Indeed, despite some examples of operational assimilation for short-range prediction, there are almost no enterprise-scale hydrologic data assimilation systems in existence today. The implementation of a proposed hydrologic data assimilation component of HEFS was deferred beyond the current version of HEFS. The National Water Model employs a routing-model data assimilation approach that adjusts streamflow, but does not attempt true hydrologic data assimilation. The Northwest RFC runs a principal-components based sub-system within CHPS to propose SWE updates for their operational models, but forecasters oversee any modifications to model states.

A sample of operational-context hydrologic data assimilation studies includes Seo, Koren, and Cajina (2003); Seo et al. (2009); Thirel, Martin, Mahfouf, Massart, Ricci, and Habets (2010); Thirel, Martin, Mahfouf, Massart, Ricci, Regimbeau, et al. (2010); Weerts et al. (2010); and DeChant and Moradkhani (2011a, 2011b). Many of these hydrologic data assimilation studies relate to short-range forecasting, but there have also been persuasive demonstrations showing skill improvements in SWE assimilation for seasonal forecasting. Huang et al. (2017) provided one of the more comprehensive illustrations for ESP forecasting in 12 western U.S. basins that an ensemble-based hydrologic data assimilation approach with NWS forecast models improved the accuracy of seasonal runoff volume

forecasts. Bergeron, Trudel, and Leconte (2016) assessed the assimilation of streamflow, SWE and snow covered area for distributed model forecasts of a watershed in Canada, finding that streamflow assimilation had a general benefit throughout the year, assimilation of point SWE observations benefitted seasonal forecasts, while assimilation of snow covered area data had little benefit.

It is clear that hydrologic data assimilation would provide a step forward for operational flow forecasting, and high-potential techniques exist that could be implemented. A particular benefit of automated hydrologic data assimilation would be to enable hindcasting that has more consistency with real-time forecasting, which would allow for more robust benchmarking and evaluation of different forecasting techniques. It thus seems prudent to invest in efforts to develop and deploy hydrologic data assimilation, particularly for seasonal forecasting (where it is more tractable than daily flood forecasting). Due to the nascent nature of the technique's applications in operational settings, it appears likely that the benefits of such development will not be immediate, and that experimentation and refinement of the implementation will be needed. The long-range potential benefit, and particularly the possibility of transforming mid-range forecast practice by enabling over-the-loop prediction, could be highly valuable.

Harnessing climate predictability

The hydrology research community has been investigating the potential for advancing mid-range forecasting through the use of climate information—either climate system states such as El Niño, or explicit climate forecasts—for several decades. Hamlet and Lettenmaier (1999) showed benefits of trace-weighting using ENSO and PDO indices for mid-range flow prediction in the Columbia River Basin, and Wood, Kumar, and Lettenmaier (2005) showed the benefits of using climate model forecasts from NCEP to enhance ESP prediction skill (though finding a benefit only in strong ENSO anomaly years). Other research efforts have confirmed the benefit of using climate forecasts from the NMME for in the generation of runoff and soil moisture predictions, both in the U.S., e.g., Mo and Lettenmaier (2014) and in Europe, e.g., Thober et al. (2015). A recent collection of over 40 papers on seasonal streamflow forecasting in the journal *Hydrology and Earth System Sciences* (Wetterhall and Di Giuseppe 2018) included a number of studies assessing the value of other climate forecast systems, such as the ECWMF System 4 and System 5, to boost the skill of mid-range climate predictions. In the U.S., as described earlier, the major pathway to use operational climate forecasts in RFC streamflow prediction is embedded in HEFS, but this pathway has been little used.

It is clear that improved sub-seasonal and seasonal climate forecasts would have substantial benefit for seasonal and longer hydrologic forecasts, with a particular need for forecasts of cool-season precipitation in the main

runoff generating regions of the western U.S such as the Upper Basin. Sub-seasonal and seasonal climate prediction has also long been a major scientific challenge, requiring large-scale investments by the Earth system research community in improved global-scale observations, climate modeling, climate model data assimilation systems, and predictability studies. Such work is underway, supported via the research and climate-services programs of agencies including NASA, NOAA, DOE, DOD, and NSF, as well as internationally by multifaceted, multinational initiatives (Chapter 7). A major community advance in recent years has been the generation of hindcasts to complement real-time forecasts, which allows for skill assessment and the training of downscaling techniques for the forecasts. Another is the development of multi-model forecast products, such as the NMME and SubX.

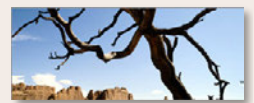
There is currently no shortage of techniques for incorporating climate information into mid-range hydrologic predictions (e.g., pre- and post-weighting methods), but the value of doing so is dependent on the skill of the input climate information. In locations where sub-seasonal and seasonal predictability is stronger, such as the Pacific Northwest and parts of California, the application of climate information can provide a moderate increase in mid-range hydrologic skill, on the order of 10-20%, depending on the forecast location, lead time, and initialization date.

The Upper Basin is well known as a region of limited skill for sub-seasonal and seasonal precipitation forecasts (Chapter 7), but there is hope that more regionally tailored, circulation-based analyses of climate variability, and climate predictability in steadily evolving climate forecast models, could lead to minor to moderate skill improvements in streamflow forecasts. Because of the sizable potential value of improved climate prediction for seasonal and longer streamflow forecasting, it is advisable to continue to monitor progress and invest in analysis and development of watershed-scale climate forecasts via both empirical and dynamical methods and sources as operational climate forecasting capabilities slowly evolve. The current state of the science and practice, and ongoing efforts to improve climate forecasts, are described more fully in Chapter 7.

Developing testbeds to investigate over-the-loop forecast approaches

NOAA currently has twelve [Testbeds and Proving Grounds](#) to facilitate the orderly transition of research capabilities to operational implementation for such phenomena as severe weather and hurricanes, but lacks a testbed devoted to hydrologic prediction. The most relevant testbed is the Hydromet Testbed hosted jointly by NOAA's Earth System Research Laboratory (ESRL) Physical Sciences Division and the Weather Prediction Center, but the focus of that testbed has long been more meteorological than hydrological. A major advance over the last decade from that testbed, for instance, was the identification and development of predictive

NOAA Testbeds



Link:

<https://www.testbeds.noaa.gov/>

capabilities related to atmospheric rivers (Chapter 2). The lack of a hydrologic forecasting testbed is a critical institutional gap, in that such a testbed that would support experimentation and systematic development of real-time forecast approaches, including new models, data assimilation techniques, post-processing approaches, model calibration techniques, climate and weather downscaling methods, verification, and communication related to forecasts and decision making. Such a testbed could support the transition of new research to operations for both the National Water Center and for the RFCs, and build the case for the viability of over-the-loop approaches.

In a piecemeal fashion, advancing individual strategies for better harnessing watershed and climate predictability will incrementally produce better forecasts, but the more fundamental challenge—and opportunity—is to build the institutional capacity in NOAA and other agencies to support steady, rational development activities over multiple years. For the most part, these will be over-the-loop approaches in which an automated system is run with various components, generating hindcasts and real-time forecasts, and can be verified and benchmarked against research variations that could potentially provide upgrades to the system. The Colorado River Basin Streamflow Testbed described earlier shows an example of what can be gained from the objective comparison of forecast variations (through post-processing) for water management outcomes, though the hydrologic forecasts themselves lie outside of the testbed. Reclamation and USACE have supported work with NCAR and partners in recent years to develop a small-scale example of such a testbed, but much larger scale, more formal, multi-agency investment is required, employing or virtually harnessing multiple full-time staff, and with strong links to operational forecast centers and stakeholder groups.

A summary of these challenges and opportunities for streamflow forecasting is provided below.

Challenge

The modeling advances over the last three decades and their demonstration in forecasting contexts have not altered the reliance of RFC operational practices on the legacy models. There is a clear scientific rationale for enhancing the physics of the legacy models in many forecast cases, yet implementing modeling advances faces major hurdles for operational flow prediction in both the current in-the-loop forecast paradigm and the over-the-loop workflow.

Opportunities

- Effective approaches for regional parameter estimation (calibration) in more complex watershed process models to enable model streamflow simulations on a par with the performance of current legacy models.

- Effective approaches for automated hydrologic data assimilation, to replace the many manual adjustments made by expert forecasters and enable skillful over-the-loop systems.
- Automated interoperability of water management decisions and river basin modeling systems, to replace the manual incorporation of management effects like releases and diversions.

Challenge

There is little question that more extensive monitoring of watershed conditions, either by direct or remote measurements, would benefit hydrologic forecasting. The benefits can arise in two ways: 1) improving real-time analyses that provide the initial conditions for forecasts, which matter most when those conditions provide most of the forecast signal, such as in late spring; and 2) improving model implementation by helping constrain model parameters and guide structural implementation of those parameters.

Opportunities

- Expansion of real time measurements of streamflow, snow water equivalent (SWE), soil moisture, and ET.
- Methodological research into how observations that are sparse or coarse (e.g., soil moisture) or collected as snapshots (e.g., ASO SWE) may be incorporated into a forecast workflow.
- Development of both real-time and multi-year (retrospective) records that provide a foundation for research and methodological verification.

Challenge

To open the door for adoption of more complex models, multi-faceted ensemble approaches, leveraging supercomputing, and other advancements in streamflow forecasting, the research and operational communities must develop effective automated hydrologic data assimilation methods.

Opportunity

- Experimentation and refinement of automated hydrologic data assimilation, particularly to enable over-the-loop prediction.

Challenge

It is clear that improved sub-seasonal (S2S) and seasonal climate predictions would have substantial benefit for mid-range hydrologic predictions, with a particular need for cool-season precipitation forecasts in the runoff-generating regions of the western U.S. Yet, S2S climate prediction has also long been a major scientific challenge, requiring large scale investments by the Earth system research community in improved global-scale observations, climate modeling, climate model data assimilation systems, and predictability studies.

Opportunity


- Invest in analysis and development of watershed-scale climate forecasts via both empirical and dynamical methods and sources as operational climate forecasting capabilities slowly evolve.

Challenge

The lack of a hydrologic forecasting testbed is a critical institutional gap. Support is needed to transition new research to operations for both the National Water Center and for the RFCs, and build the case for the viability of over-the-loop approaches.

Opportunity

- A testbed would support experimentation and systematic development of real-time forecast approaches, including new models, data assimilation techniques, post-processing approaches, model calibration techniques, climate and weather downscaling methods, verification and communication related to forecasts, and decision making.



Volume IV

Long-term—Informing the 5-Year to 50-Year Time Horizon

Chapter 9. Historical Hydrology

Chapter 10. Paleohydrology

Chapter 11. Climate Change-Informed Hydrology

Volume IV of the Colorado River Basin State of the Science report focuses on models and methods for developing hydrologic traces that represent plausible hydrologic futures and can be run through system or planning models to evaluate the potential for outcomes and impacts of interest over the next 5 to 50 years. The three main approaches for developing such traces are Historical Hydrology (Chapter 9), Paleohydrology (Chapter 10), and Climate Change-informed Hydrology (Chapter 11). Long-term hydrologies generated using one or more of these approaches are used as driving inputs for Reclamation's CRSS planning model, as well as similar planning and system models used by other organizations. The three chapters in Volume IV provide comprehensive descriptions and assessments of the respective approaches and their variants, the data they require, their applications, and their tradeoffs. It is important to examine and understand these choices in order to select appropriate hydrologic traces for system modeling and risk, and also to interpret the output of system modeling that has already been performed.

Traditional long-term planning methods are based on the assumption that future hydrology will have characteristics (average, variance, extremes) similar to the historical observed hydrology. The extreme hydrologic drought of 2000–2004, unprecedented in the observed record, highlighted the downside of basing expectations for future hydrology only on the observed record (i.e. historical hydrology). Clearly, hydrologic behavior outside the range of the past 100 years was, and is, possible. Accordingly, the system analyses performed by Reclamation to support the 2007 Interim Guidelines included, for the first time, ensembles of hydrologic traces based on tree-ring reconstructions of basin paleohydrology. These traces show a broader range of natural variability, including more severe and sustained droughts, than those based only on the past century's observed hydrology (Chapter 2).

As the dry period that began in 2000 persisted, studies modeling the future impacts of human-caused climate change on basin hydrology consistently indicated that the 21st century was likely to see systematic shifts in hydrologic conditions: earlier snowmelt and runoff, lower runoff efficiency, and (with less certainty) a decline in annual streamflow. Because Reclamation and other basin stakeholders saw the need to explicitly represent this additional climate change risk in planning studies, Appendix U in the 2007 Interim Guidelines laid out a pathway for developing and using climate change-informed hydrologic traces. In 2012, the Basin Study formally incorporated a climate change-informed ensemble along with traces based on historical hydrology and paleohydrology, using Robust Decision Making techniques to assess risks from all scenarios on an equal footing.

As with the historical hydrology and paleohydrology, a typical analysis of climate change-informed hydrology will outline an ensemble of potential future trajectories for basin hydrology. Over longer planning horizons (30 years or more), the range depicted by this ensemble is even broader than those depicted by historical hydrology and paleohydrology, most notably on the dry side of the distribution.

Several planning studies for the basin have used hydrologic traces that effectively blend information from two or more types of hydrology; these are described in greater detail within the listed chapters:

- “Paleo-conditioned” hydrology takes state-transition (wet-dry) information and resamples the historical hydrology to create new sequences that reflect paleo-variability (Chapter 10)
- Delta-method statistical downscaling takes future change factors in temperature and precipitation from climate-model ensembles and perturbs the historical climate sequence to simulate the historical hydrologic variability recurring under future climate (Chapter 11)
- Temperature-perturbed hydrology is similar to the above, but uses several prescribed temperature change factors to simulate the historical hydrologic variability recurring under a warmer climate, assuming no precipitation changes (Chapter 11)

While the sequence of the three chapters may suggest an evolution or transition, it would be incorrect to conclude that climate change-informed hydrology is now the preferred or optimal source of long-term traces to drive system models for planning studies. All three main sources of hydrologic ensembles (historical, paleohydrology, climate change-informed) have inherent advantages and limitations, summarized in the table below. These attributes may be more or less relevant depending on the time horizon of a risk assessment. For example, assessing risk five years into the future would not need to account for the sources of future uncertainty that longer-term studies must grapple with. For long-term risk assessments, it is more helpful to base analyses on at least two, and ideally all three types of hydrology, than any single type; more specifically, it is inappropriate to assume the historical hydrology will repeat itself. To further reduce the impacts of the assumptions inherent to any ensemble, it may be beneficial to use advanced analytical and decision-support frameworks that deemphasize probabilistic risk.

Key characteristics of the main types of hydrology, observed, paleohydrology, and climate change-informed. (Source: adapted from Lukas et al. 2014)

	Historical hydrology (Chapter 9)	Paleohydrology (Chapter 10)	Climate change-informed hydrology (Chapter 11)
Most useful information to extract from this type of hydrology	Variability (interannual to decadal); recent trends	Variability (interannual to multi-decadal); shifts in mean and variability	Potential long-term future changes
Embedded assumption in using this to inform planning	Historical mean and variability is stable over time and is representative of future risk	Pre-1900 hydrology, including severe droughts and shifts in mean and variability, can recur in the future	Climate models can provide reliable information about future changes in the basin
Key data and models	Gaged observations of streamflow and major diversions; water-balance model to naturalize streamflow (except at headwaters gages)	Tree-ring chronologies (site time-series); statistical models relating ring-width to climate and hydrology	Global climate models, statistical downscaling and bias-correction methods; gridded climate data; regional climate models; hydrology models
Advantages	Provides baseline information about risk; relates other sources of information to our experience of system impacts; readily available, trusted, and well-vetted	Shows broader range of natural variability than seen in the observed records; places observed variability in longer context; provides many sequences of wet and dry years	Best source of information about potential effects of future climate change on hydrology
Limitations	Does not capture the full range of natural variability; does not reflect risk from future climate change; likely to underestimate future system stresses	Uncertainty in the proxy information; does not reflect risk from future climate change, though the broader range of variability may approximate that risk	Larger uncertainties in future changes, requiring consideration of many traces; complex datasets that are difficult to obtain, analyze and interpret
Primary sources of uncertainty affecting the output	Imperfect record of streamflows; inadequate characterization of depletions when naturalizing gage records	Tree rings imperfectly reflect hydroclimatic conditions; choices in handling of the tree-ring data and the model that relates tree-ring data to observed streamflows	Future emissions of greenhouse gases; differing climate models; choice of downscaling and bias-correction methods; differing hydrologic models



Chapter 9

Historical Hydrology

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Key points

- The observed historical streamflow record is used to generate ensembles of streamflow traces for input into system models for long-range planning, as well as to validate and calibrate paleohydrology and climate change-informed hydrology.
- Multiple methods have been used to generate Colorado River Basin streamflow traces for system analysis; each has advantages and limitations and none is a clear best choice for all applications.
- The index sequential method (ISM), which has been the most common method used in Reclamation system analyses for decades, has advantages but also significant limitations, most of which center on the fact that ISM traces do not deviate from the observed historical record.
- Stochastic alternatives to ISM have been used to produce ensembles of traces that maintain many characteristics of the historical record while offering novel ranges, durations, and frequencies of flows.
- Stochastic methods that are based on statistical summaries of the historical data, known as parametric methods, have the advantage of being able to generate values beyond the range of the observed record, but require assumptions about the underlying form of the population of streamflows.
- Stochastic methods that are based on sampling directly from the historical data, known as nonparametric methods, do not require assumptions about the underlying form of the population of streamflows but are sensitive to the number of observations from which to sample.
- Research trends are toward nonparametric methods of streamflow generation and toward hybrid methods that use historical hydrology with reconstructed tree-ring hydrology or climate change-informed hydrology.

9.1 Introduction

All long-term system planning studies in the Colorado River Basin use the observed historical streamflow record, naturalized as described in Chapter 5, in one way or another. For several decades, the historical record has been used directly to generate streamflow traces for input to Reclamation's long-term planning models. The evolution of methods that use the historical record directly and the current state of long-term synthetic streamflow based on historical hydrology are described in this chapter. Methods that use the historical record to calibrate, validate, and synthesize paleohydrologic and climate change-informed streamflow traces are described in Chapters 10 and 11, respectively.

Concerns have been raised for decades that the historical record may not adequately represent long-term future hydrologic risk (Tipton and Kalmbach 1965). The full record of naturalized streamflows, which currently spans 1906 to 2018, is considered particularly problematic because it includes an extraordinary period of high flows in the early 20th century (Chapters 2 and 5). The full record also has limited representation of prolonged droughts, which research indicate have been more common in the distant past and could become more common in light of climate change (Chapter 10).

Historical hydrology is useful as a baseline to provide context for future risk; however, as conditions increasingly deviate from the observed past, there is less confidence in studies that use historical hydrology alone (Naggettini 2016). According to Vogel (2017),

“Due to the now widespread acceptance that hydrologic systems often have and will undergo significant change, it is no longer reasonable to plan our future water resource systems by assuming that future conditions will replicate past hydrologic experience.”

These concerns carry through to any system model streamflow inputs generated purely from the full observed record, but as this chapter will describe, some methods are more constrained by characteristics of the observed hydrology than others.

This chapter uses terminology that may be unfamiliar to some readers. Four terms in particular, *parametric*, *nonparametric*, *stochastic*, and *deterministic*, warrant definition up front. Figure 9.1 helps illustrate the explanations provided here. It contains a histogram with bins of annual natural flows at Lees Ferry from 1906–2016 along the x-axis and the frequency of occurrence of the flows in each bin on the y-axis. The curves on the figure are continuous theoretical probability density functions (PDFs) fit to the empirical data. Each function, or equation, provides the probable frequency of any value of annual streamflow, and is made particular to this set of observations by *parameters*, such as mean and standard deviation, which identify the location and scale of the distribution, respectively.

The green line on Figure 9.1 is the “normal” PDF. Normal PDFs are also known as bell curves because they are symmetrical on either side of the mean of the data. The normal curve is estimated from two parameters, mean and standard deviation, calculated from the observed data. Another distribution, the Johnson SB distribution, shown in blue on the figure, uses two additional parameters, skew (symmetry) and kurtosis (how quickly the tails approach zero), also calculated from the observations, to further refine

the distribution. Of 50 theoretical distributions tested on this set of annual flows at Lees Ferry, the Johnson SB distribution has the best fit to the observed data, but it is not a distribution typically used in streamflow synthesis. The lognormal distribution, which can use either 2 or 3 parameters (mean and standard deviation, plus or minus skew), is shown on the figure to illustrate the discussion about parametric stochastic methods later in this chapter. The lognormal distribution, though it may not always be the best fit distribution, is often used in hydrologic studies.

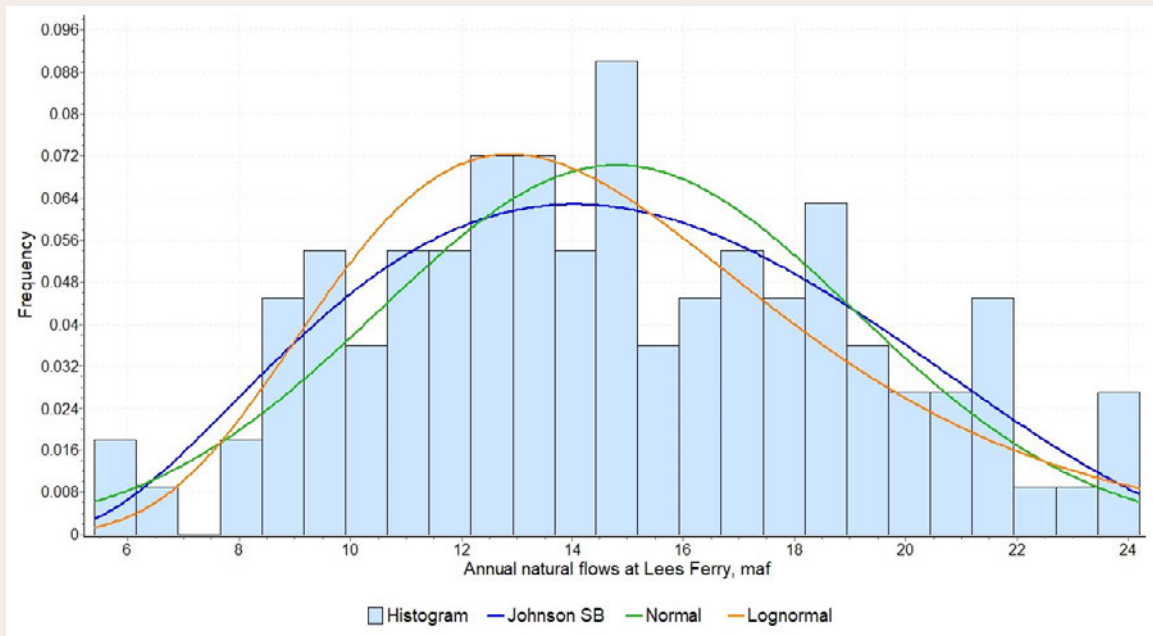


Figure 9.1

Probability density function of annual natural flows at Lees Ferry (1906–2016), in million acre-feet. (Data: Reclamation. Figure generated with [EasyFit by MathWave](#).)

Approaches to synthetic streamflow generation that use the PDF as their basis, and therefore rely on parameters derived from the observed data, are called *parametric* approaches. These approaches are considered parsimonious because they rely on a summary of the observations, rather than the set of observations themselves (Scott 2015). Approaches that use the observed data directly, without relying on an estimated, parametric PDF, are called *nonparametric* approaches.

Parametric approaches have the advantage that they can be used when only a short record is available, or when observations at the extremes are few or non-existent, whereas nonparametric methods use the data at hand and are thus limited by the range of observations, though this limitation has been addressed in some nonparametric methods (Loucks and van Beek

2017). Nonparametric methods have the advantage of not requiring any information or assumptions or about the underlying probability distribution, and therefore are able to reflect processes that might not be represented by an assumed distribution.

Stochastic approaches to synthetic streamflow generation explicitly include uncertainty by incorporating a random component in the generation process. In stochastic approaches, the same set of inputs will result in different outputs. *Deterministic* approaches do not have a random component—the outputs are fully determined by the inputs. Stochastic approaches have the advantage of producing novel combinations of streamflow events and durations. Deterministic approaches, on the other hand, are useful when including streamflow uncertainty would be detrimental to an analysis, for example, while other, non-hydrologic variables are being tested.

9.2 Index Sequential Method

The Index Sequential Method (ISM) is a nonparametric, deterministic approach used to generate multiple streamflow time series directly from the historical, natural flow record. It was first applied by Reclamation 50 years ago to add variability to the observed hydrologic record, though the label “Index Sequential Method” was attached to the method sometime later (Reclamation 1969; Cowan, Cheney, and Addiego 1981). ISM is the method most often used in Reclamation’s risk analyses.

Typically, ISM traces are sampled blocks of data from the full, historical natural flow record. The 1906–2017 record is used in examples in this chapter, but Reclamation has updated the record to 2018. The trace lengths correspond to the planning horizon under study. For example, a modeling study for years 2020 to 2060 would use traces that were 41 years long. The number of unique traces that can be generated from the record with ISM equals the number of years in the record (112 traces from the 1906–2017 record). The steps in generating ISM traces are described in the next paragraph and illustrated in Figure 9.2.

Using ISM, the first generated trace (Trace 1 in Figure 9.2) is equivalent to the historical record, beginning at the record’s first year (usually 1906 but can be other years depending on the study goals) and ending with the year corresponding to the desired trace length. For each additional trace, the start year is advanced by one year and one year of historical data is picked up at the end of the trace (Traces 2–72). Each additional trace steps forward and eventually reaches the end of the full natural flow record (Trace 72).

When the end of the natural flow record is reached before the end of the planning horizon, the start year of the natural flow record is repeated by

appending it to the end (Trace 73). This wrapping is repeated for each additional trace, with the start year advanced by one year and another year from the beginning of the natural flow record wrapped back to the end, until the desired number of sequences is obtained or the original, historical ordering reoccurs.

With ISM, the historical, year-to-year streamflow sequence is preserved in each trace except when wrapping occurs. Following the steps described above for traces that contain wrapping (Traces 73–112), a junction between the original end year and the original start year is introduced, as in Trace 73, creating an ordering of flows not seen in the historical record. Traces generated by ISM are therefore sensitive to the chosen start year—wrapping that year’s natural flow to the end of a trace can impact whether hydrologic conditions rebound, stay about the same, or fall deeper into drought.

Because each ISM trace is shifted by one year relative to the previous trace, it is possible to study how starting with different inflow values impacts the system. The ensemble of streamflow traces generated with the ISM example provided in Figure 9.2 is shown below in Figure 9.3. The figure illustrates the repetitive sequencing and bounds of traces generated with ISM.

Model year	Natural flow record year	Trace 1	Trace 2	Trace 3	...	Trace 72	Trace 73	Trace 74	...	Trace 111	Trace 112
2020	1906	1906	1907	1908		1977	1978	1979		2016	2017
2021	1907	1907	1908	1909		1978	1979	1980		2017	1906
2022	1908	1908	1909	1910		1979	1980	1981		1906	1907
⋮	⋮	⋮	⋮	⋮	↗ ↗	⋮	⋮	⋮	↗ ↗	⋮	⋮
2058	1944	1944	1945	1946		2015	2016	2017		1942	1943
2059	1945	1945	1946	1947		2016	2017	1906		1943	1944
2060	1946	1946	1947	1948		2017	1906	1907		1944	1945

Figure 9.2

Index Sequential Method (ISM) example that uses the natural flow record (1906-2017) and modeling horizon of 41 years (2020-2060). The method is described in the text. (Source: adapted from Reclamation)

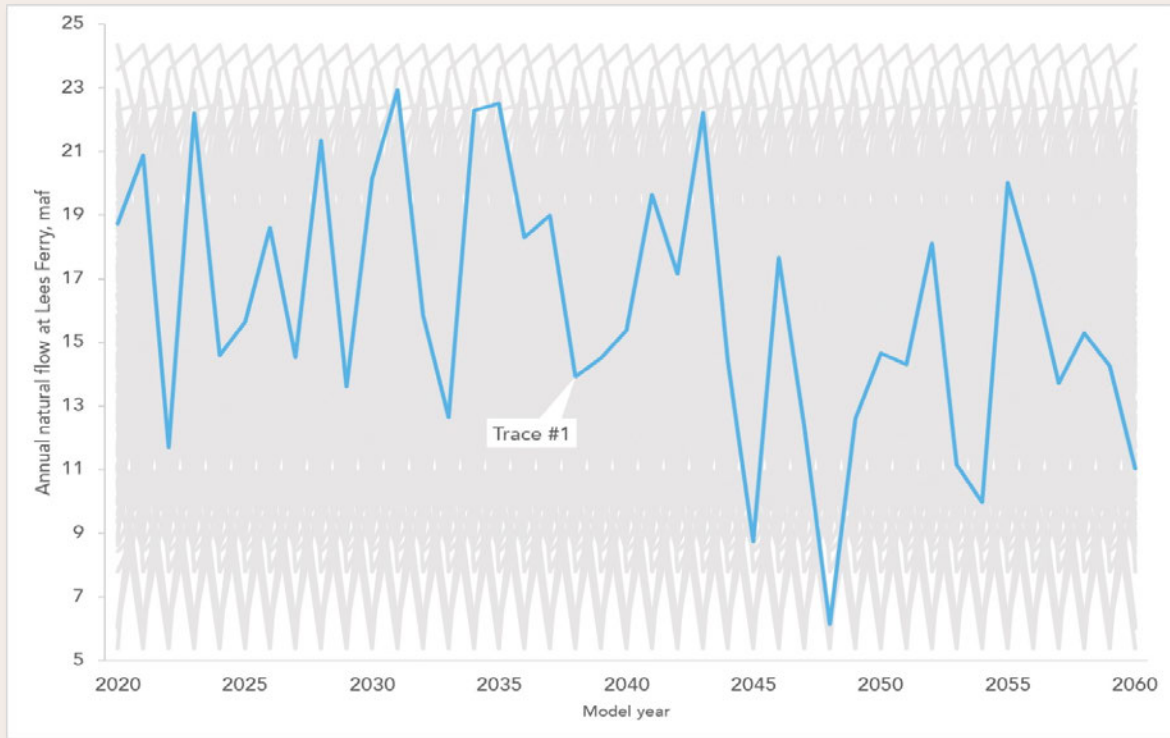


Figure 9.3

Example ensemble of 112, 41-year natural flow traces for the Colorado River at Lees Ferry generated with ISM as described above. The blue line shows Trace #1 in Figure 9.2: the natural flows from 1906-1946. (Data: Reclamation)

Advantages and limitations of ISM

Like the other methods described in this report that are used to develop hydrologic inputs to Reclamation's operations and planning models, ISM has advantages and limitations; a summary is given in Table 9.1 and discussed in the text below.

The primary advantage of ISM is that, by using the naturalized historical hydrology directly, it reflects the physical processes, climatological conditions, and watershed characteristics that were in place when the streamflow observations were made. There is little concern that traces sampled directly from the historical time series might misrepresent the processes, conditions, or characteristics that combined to produce the those streamflows. From that primary advantage follow some of the additional benefits listed in Table 9.1: ISM preserves the characteristics of the historical time series, i.e., it preserves the cross-correlations among basin locations, serial correlations from year to year, persistence from month to month, and the mean, variability, and other statistics of the historical record.

Table 9.1

Summary of advantages and limitations of using the index sequential method

Advantages	Limitations
Retains credibility because it is based on observed values	Full record includes the unusually wet years of the early 20 th century—though sub-periods from the full record are often used
Preserves the historical frequency distribution and summary statistics	Cannot generate event magnitudes, durations, or frequencies outside of the observed record
Nonparametric, so not subject to errors in distribution fitting	Does not provide enough variety of “statistically plausible” potential sequences for planning analyses (Prairie et al. 2006)
Preserves historical persistence and spatial relationships, i.e., autocorrelations and cross-correlations	Cannot represent changes to relationships and dependencies that may arise from future climate change
Allows systems analysis under alternative initial inflows	Statistical interpretations of results are complicated due to lack of independence or randomness of traces
Traces are reproducible	Limited representation of uncertainty

The primary limitation of ISM is the converse of its advantage: it limits analyses to the streamflow ranges, durations, and frequencies seen in the historical record. ISM is not a stochastic method and therefore novel streamflows are not produced. As Kendall and Dracup (1991) explain,

“Streamflow is a random process. The historic hydrologic record is one realization of this random process. Wrapped hydrologic sequences of the historic record are not other realizations of a random process in a strict sense even though they are treated that way when probability curves are developed.”

Nor are the sequences independent (Labadie et al. 1987; Ouarda, Labadie, and Fontane 1997). Ouarda et al. warn that, “An additional concern with ISM has been the statistical dependency of the extracted sequences because of the overlapping structure of synthetic data records generated.” One hundred twelve ISM traces generated from a single, 112-year sample are not the same as 112 independent streamflow traces. In statistical terms, the traces are very highly correlated with each other—a phenomenon one would not encounter outside of the ISM technique (Staschus and Kelman 1989). According to Salas (1992), “A major drawback with this procedure [ISM] is that the resulting set of N input series yields N outputs which are not independent and, as a consequence, the outputs have less precision.”

The lack of randomness and independence, two basic premises for statistical analysis of hydrological time series (Naghetini 2016), can be illustrated with a graph of the low-flow sequences found in the example traces used in Figure 9.2 and Figure 9.3. In Figure 9.4, the minimum 5-year average streamflow at Lees Ferry for each trace is shown as a single bar. The lowest 5-year minimum, 9.55 maf, which corresponds to the calendar year 2000–2004 annual average, reoccurs in 37 of the 112 traces.

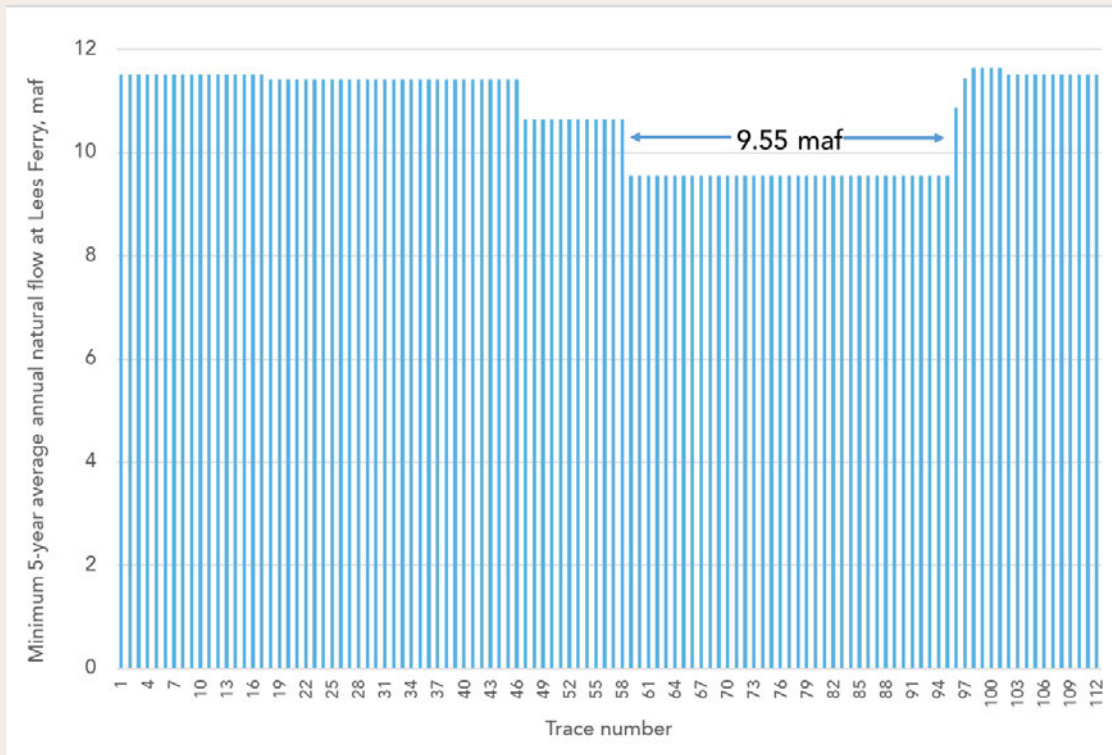


Figure 9.4

Minimum 5-year average annual flow at Lees Ferry in each of 112 ISM traces generated from the full natural flow hydrology (1906–2017) and the 2020–2060 planning horizon. (Data: Reclamation)

The chart shows that there are a handful of unique 5-year minima, not dozens of different 5-year minima as might be expected from an ensemble of independent traces of a continuous random variable like streamflow.

Consideration should be given to how ISM results are interpreted. ISM provides the odds of a particular outcome only if history repeats itself. ISM does offer multiple, different streamflow traces. The hazard is that tests of the system against an ensemble of ISM traces might be interpreted as tests of a random distribution of future events, reflecting the uncertainties inherent in natural variability. Srinivas and Srinivasan (2005) consider ISM to be a simple technique that may not model the data adequately, motivating the development of new multi-site methods.

Even so, the value of ISM's preservation of streamflow correlations in both time and space in the Colorado River Basin should not be underestimated. Reproducing the significant correlations throughout the basin using parametric methods is not a trivial exercise. See Lee and Salas (2006) for a breakdown of all the month-by-month and site-to-site cross-correlations among the 29 inflow points in Reclamation's Colorado River Simulation System (CRSS) model and a description of their efforts to extend the natural flow record while maintaining those correlations. Nowak et al. (2010) also discuss the drawbacks of taking a parametric approach to disaggregating synthetic sequences in time and space.

ISM applications

The conception of ISM and its application in the Colorado River Basin coincided with advances in computing power. The first documented ISM-type application is found in Reclamation's 1969 "Report of the Committee on Probabilities and Test Studies to the Task Force on Operating Criteria for the Colorado River," in which test streamflow sequences were described that were created by wrapping the beginning of the historical record to the end. Multiple test sequences, including ones selected to stress the system, were used in 146 computer runs to study various demand and operations scenarios (Reclamation 1969).

Since then, ISM-generated inflow sequences have been used as inputs to the Colorado River Simulation Model (CRSM) and its successor, CRSS, and have provided the primary basis for Colorado River Basin planning for several decades (see Chapter 3 for descriptions of these models). Most of the studies have involved sampling blocks from the full natural flow record that starts in 1906. The assumption implicit in the use of the full record is that the observed long-term mean and variance of natural flows in the Colorado River Basin are stationary and representative of the future. However, ISM traces that are sampled from the full record contain the wet period of the early part of the 20th century, which, in the context of the paleohydrologic record (see Chapter 10), is one of the wettest sequences in the past 1200 years. The mean annual flow from 1906 to 1925 is about 17.9 maf, well above the full record mean of 14.8 maf and over 30% above the most recent 30-year mean of 13.3 maf.

To address the issue of repeating the unusually wet years of the early 20th century in simulations, Reclamation has explored applying ISM to other segments of the hydrologic record (Table 9.2). Most recently, in response to an extended drought and the need to support drought contingency planning efforts, Reclamation and stakeholders in the basin identified 1988 to 2016 as a period that could provide more perspective on system risks (see Table 9.2). This sequence of years is referred to as the "Stress Test" hydrology. It is compared to the full record in Figure 9.5.

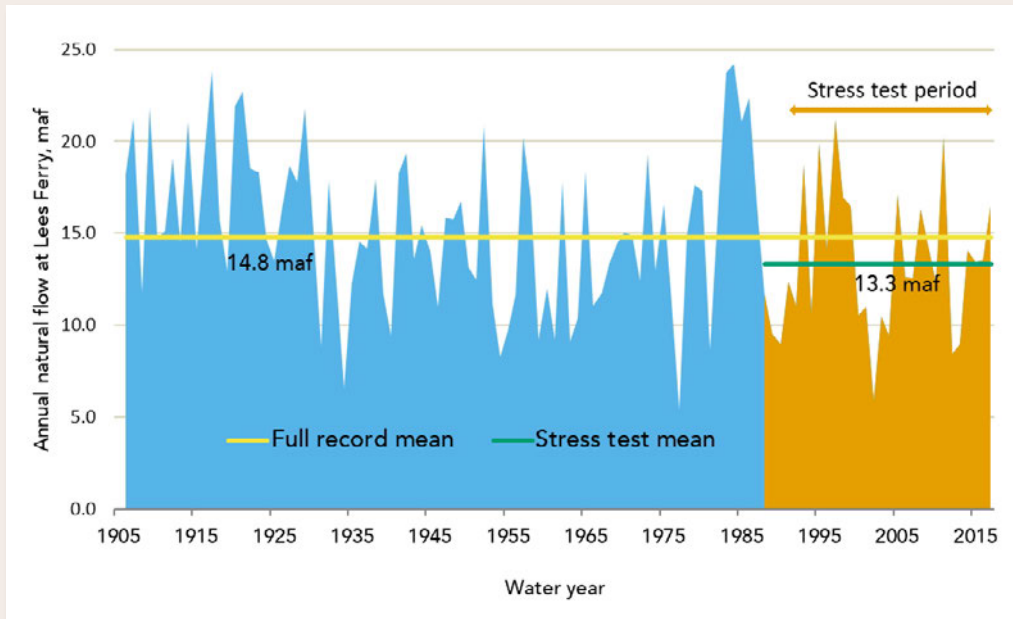


Figure 9.5

Full-record and stress-test period annual natural flows at Lees Ferry (1906-2017). (Data: Reclamation)

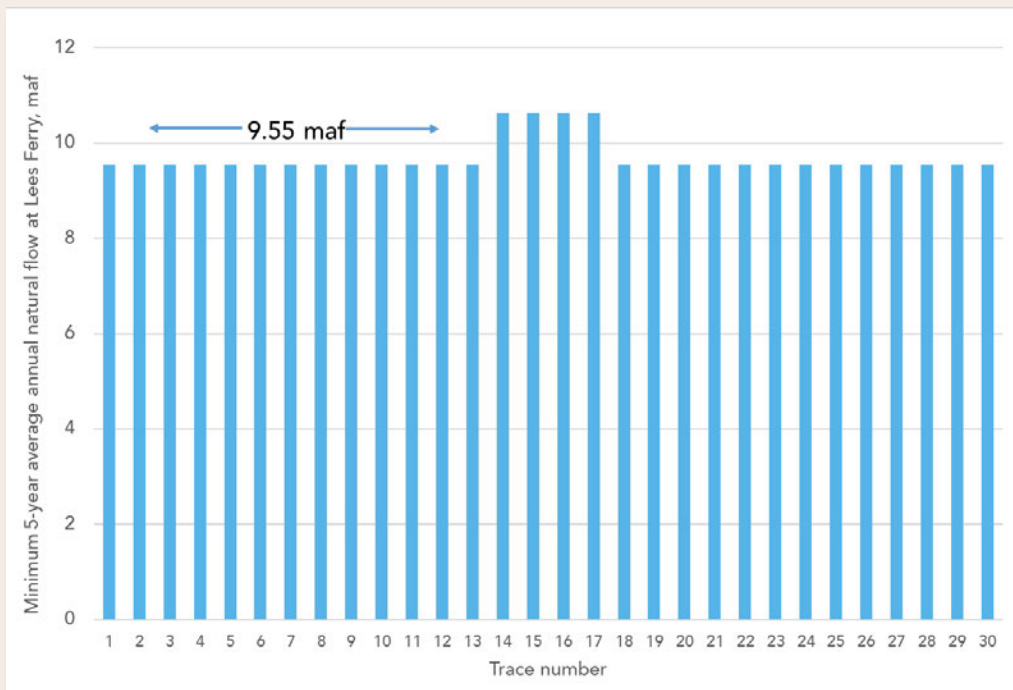
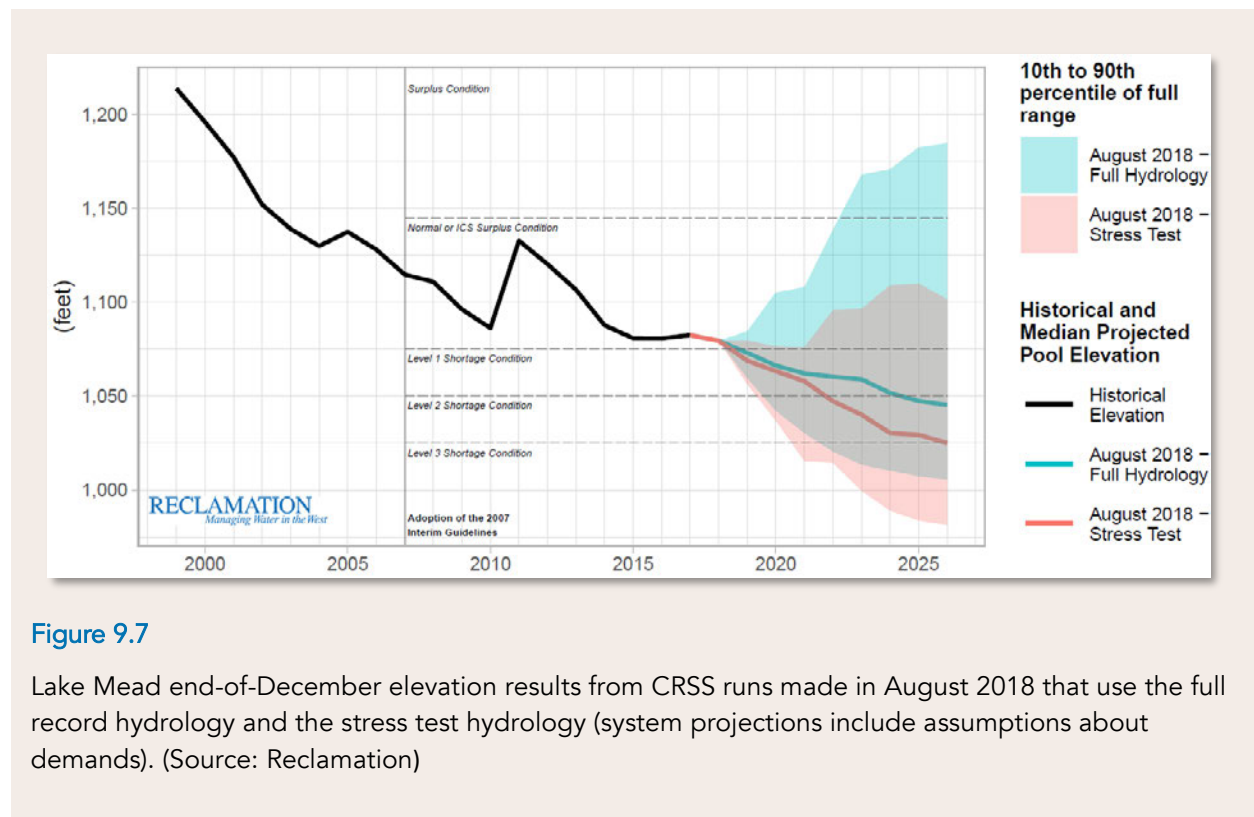


Figure 9.6

Minimum 5-year average annual flow at Lees Ferry in each of 30 ISM traces generated from the stress test natural flow hydrology (1988–2017). (Data: Reclamation)

The stress test trace length (2020–2049) contains the same number of years as those in the stress test hydrologic record (1988–2017, 30 years), so each of the 30 ISM traces contains the same streamflow values and has identical means, variances, maxima and minima. The minimum 5-year flow sequence in the stress test hydrology is shown in Figure 9.6. Again, the drought of 2000–2004 is repeated, in this case, in 26 out of the 30 traces. However, because the stress test period does not include the high flow years of earlier parts of the record, the stress test traces do not offer the same storage recovery opportunities as ISM traces generated from the full record.

An example of results from CRSS runs made in August 2018 with these two ISM inflow datasets (full hydrology and stress test hydrology) is shown in Figure 9.7. The system projections in the figure include assumptions about demands. The figure shows projected Lake Mead elevations for water years 2018 to 2026, when the Interim Guidelines will be reviewed (U.S. Secretary of the Interior 2007).



Recent Reclamation studies and reports that have relied at least partially on ISM-generated inflows are summarized in Table 9.2.

Reclamation and others have recognized the need to test Colorado River Basin operations under novel hydrologic scenarios (Prairie et al. 2006). The concern has been that the observed historical record, with or without ISM, does not adequately represent the river’s natural variability and therefore the vulnerability of the system to severe, low-frequency events. To address

this concern, other methods that use the historical hydrology, specifically stochastic methods, have been pursued. Those methods are described in the next section. Methods that use paleohydrology or climate change-informed hydrology are described in Chapters 10 and 11, respectively.

Table 9.2

Summary of recent reports and analyses that have used ISM on the observed natural flow record.
(Source: Reclamation)

Report or Analysis	Scenario Name	Years Included in ISM	Mean, maf	Planning Horizon	Number of Traces	Trace Lengths (years) ⁵
Final EIS: Colorado River Interim Guidelines for Lower Basin Shortages and Coordinated Operations for Lakes Powell and Mead ¹ , 2007	Direct Natural Flow Record	1906–2005	15.0	2008-2026	100	53
Colorado River Basin Water Supply and Demand Study ² , 2012	Observed Resampled	1906–2007	14.9	2012-2060	102	49
Minute 323 Binational Negotiations	Pluvial Removed	1931-2012	14.0	2017-2026	82	44
Ten Tribes Partnership Tribal Water Study ³ , 2018	Observed Natural Flow Record	1906-2015	14.8	2017-2060	110	44
Drought Contingency Planning ⁴ , 2019	Full Hydrology	1906-2016	14.8	2020-2026	111	41
	Stress Test Hydrology	1988–2017	13.2	2020-2026	30	30

¹The Final EIS also applied ISM to the 1244 year long paleo record.

²The Basin Study used multiple hydrology scenarios including ISM applied to the paleo record, a hybrid approach combining the paleo and observed records, and climate change based hydrology.

³The Tribal Water Study also used climate change based hydrology.

⁴The Drought Contingency Planning process took six years. The years that ISM was applied to and the planning horizon reflect those used at the end of the process (Spring 2019).

⁵In some cases, the length of the traces extend beyond the planning horizon so that continued effects of a policy can be understood, even if they extend beyond the years the policy is in effect.

9.3 Stochastic methods

The concept that natural streamflow is the result of random processes is fundamental to stochastic hydrology methods. The historical record is a single realization of those random processes, and though we can be fairly certain that the historical streamflow time series will not recur, it contains information that can be extracted and applied in the generation of novel streamflow traces. Stochastic hydrology methods use that extracted information to generate new streamflow traces, simulating the random nature of streamflow time series while maintaining fidelity to many characteristics of the historical record. By generating multiple unique, equally likely traces, these methods address the uncertainty inherent in the natural processes that result in streamflow (Bras and Rodríguez-Iturbe 1985). Generally speaking, parametric stochastic methods attempt to reproduce the statistical properties, particularly mean and variance, of the historical data. Nonparametric stochastic methods use the data at hand, and thereby also maintain fidelity to the historical data without requiring assumptions about the underlying probability distribution. Both categories offer the opportunity to look at longer and more intense sequences of low (or high) flows. See Loucks and van Beek (2017) and (Vogel 2017) for recent overviews of stochastic streamflow generation methods.

Reclamation has been exploring the use of stochastic hydrology for input to its long-term planning models since the 1970s, including supporting development of LAST (Lane's Applied Stochastic Techniques), a computer package for generating stochastic streamflow traces (Reclamation 1985; Lane and Frevert 1988; Frevert and Cheney 1988), and SAMS (Stochastic Analysis Modeling and Simulation; Salas et al. 2001; Sveinsson et al. 2007). Another stochastic streamflow generation package, SPIGOT, was developed at Cornell (Grygier and Stedinger 1990) and applied to the Colorado River by Kendall and Dracup (1991), and by Tarboton (1994) in the Severe Sustained Drought studies (Powell Consortium 1995). See Table 9.3 for more information about applications of these packages in the Colorado River Basin. All of these packages use parametric methods.

Parametric stochastic methods

As explained at the beginning of this chapter, parametric approaches require mathematical approximation of the form of the underlying distribution; i.e., a particular PDF that fits the observed streamflows and is therefore assumed to represent the larger population of streamflows of which the observed record is a sample. If the observations were normally distributed, stochastic traces could be generated by simply applying normally distributed random noise to the PDF equation. However, hydrologic data are rarely normally distributed (e.g., they are typically non-negative), so they must be normalized or transformed prior to application of a normal random term. The PDF that fits the observations indicates the

transformation method. For example, observations that are lognormally distributed (i.e., the PDF is lognormal, Figure 9.1) are transformed by taking the log of the observations. The parameters of the transformed observations are determined and used, with a stochastic component (i.e., the random noise), to generate intermediate stochastic values that are then back-transformed to yield a final, stochastic streamflow trace. In the lognormal example, the final stochastic streamflow values are obtained by taking the antilog of intermediate stochastic values (US Army Corps of Engineers 1971). The back-transformation step may not faithfully preserve the historical statistics, however, because the procedure reproduces the statistics of the transformed observations rather than those of the actual (un-transformed) observations (Tarboton 1994).

These are the basic steps of parametric stochastic streamflow generation. Refinements to better approximate real-world streamflows include incorporating persistence, or serial correlations, especially for shorter time steps, and spatial correlations for multi-site applications. The stochastic streamflow trace may simulate multiple inflows to a larger system, or it may simulate a large streamflow downstream of one or more confluences. In these cases, aggregation or disaggregation of generated traces may be required. Further refinements to incorporate parameter uncertainty have also been made. Background on the evolution and application of parametric stochastic streamflow methods can be found in Marco, Harboe, and Salas (1993) and Vogel (2017).

One of the primary challenges facing water resources researchers and planners in applying the basin's historical time series is how to use it to generate streamflow traces that allow study of the non-stationary hydroclimate. Parametric stochastic approaches to addressing non-stationarity that rely exclusively on historical hydrology focus on modifying the parameters of the PDF derived from historical observations. This approach, in a highly simplified example, entails representing the non-stationarity with a new estimate of mean annual flow, which shifts the historical, observed PDF to the right or left along the x-axis (Figure 9.1). Stochastic flows are then generated using that relocated PDF. However, this assumes that both the choice of PDF (lognormal, gamma, etc.) remains the correct one, and that the other parameters that describe that PDF stay the same. In other words, it assumes that only the average is affected by the changed conditions, and that the scale and shape of the distribution, i.e., the variance and symmetry, are stationary. If the stochastic model includes temporal or spatial correlation terms, consideration must be given to the stationarity of those components as well. Serinaldi and Kilsby (2015) summarize these considerations and additional uncertainties associated with this approach to non-stationarity. Bender, Wahl, and Jensen (2014), who looked at Rhine River flows, demonstrated a method to diagnose the

dependencies among distribution parameters. Khaliq et al. (2006) offers an extensive review of parametric approaches to non-stationarity.

Limitations

The advantages of parametric methods were identified at the beginning of this chapter. The limitations of parametric stochastic approaches include: 1) there is at least some loss of fidelity to the original data's characteristics through the transformation steps; 2) the observations may not clearly fit any of the common probability distributions or are multimodal; 3) disaggregation in time or space may require very large numbers of parameters; 4) potentially unrealistic, even negative, values may be generated; 5) nonlinear relationships are not represented, e.g., temporal and spatial correlations may vary in wet or dry episodes; 6) large samples cannot repair the bias in an incorrectly specified PDF; and 7) the implicit assumption of stationarity may be inappropriate (Salas et al. 1980; Tarboton 1994; Lall 1995; Sharma, Tarboton, and Lall 1997; Prairie et al. 2006; Milly et al. 2008; Scott 2015; Naghettini 2016; Vogel 2017).

Comparisons to ISM

Labadie et al. (1987), Frevert and Cheney (1988), Staschus and Kelman (1988), Kendall and Dracup (1991), and Ouarda, Labadie, and Fontane (1997) each compared the use of ISM with parametric stochastic methods. Most of the studies came to the conclusion that ISM is a reasonable technique for the purposes to which they were applied (primarily for analysis of hydropower and reservoir operations) and yielded similar results to stochastic techniques. Frevert and Cheney (1988) did not offer an overall assessment but cautioned that practitioners should understand that the variability in the ISM traces could be too low, citing streamflow records that are frequently broken. Ouarda, Labadie, and Fontane (1997) concluded that ISM is a valid procedure. Staschus and Kelman (1989) and Kendall and Dracup (1991), who used SPIGOT to generate stochastic traces and compared them to ISM traces, point out that, though their studies demonstrated that ISM was adequate or superior for the applications they examined, for studies looking at the extremes, or tails, of a distribution, other approaches may provide a more accurate representation. Finally, because parametrically derived streamflow traces are generated from probability distributions, probabilistic interpretations are straightforward and results lend themselves to estimates of confidence limits (Naghettini 2016) while this is not true of ISM-generated traces.

The studies that have used parametric stochastic methods on Colorado River Basin historical flows are summarized in Table 9.3. In the past twenty years, the number of such studies has fallen off; most of the research since the late 1990s that uses stochastic approaches to streamflow generation in the basin has focused on nonparametric methods.

Nonparametric stochastic methods

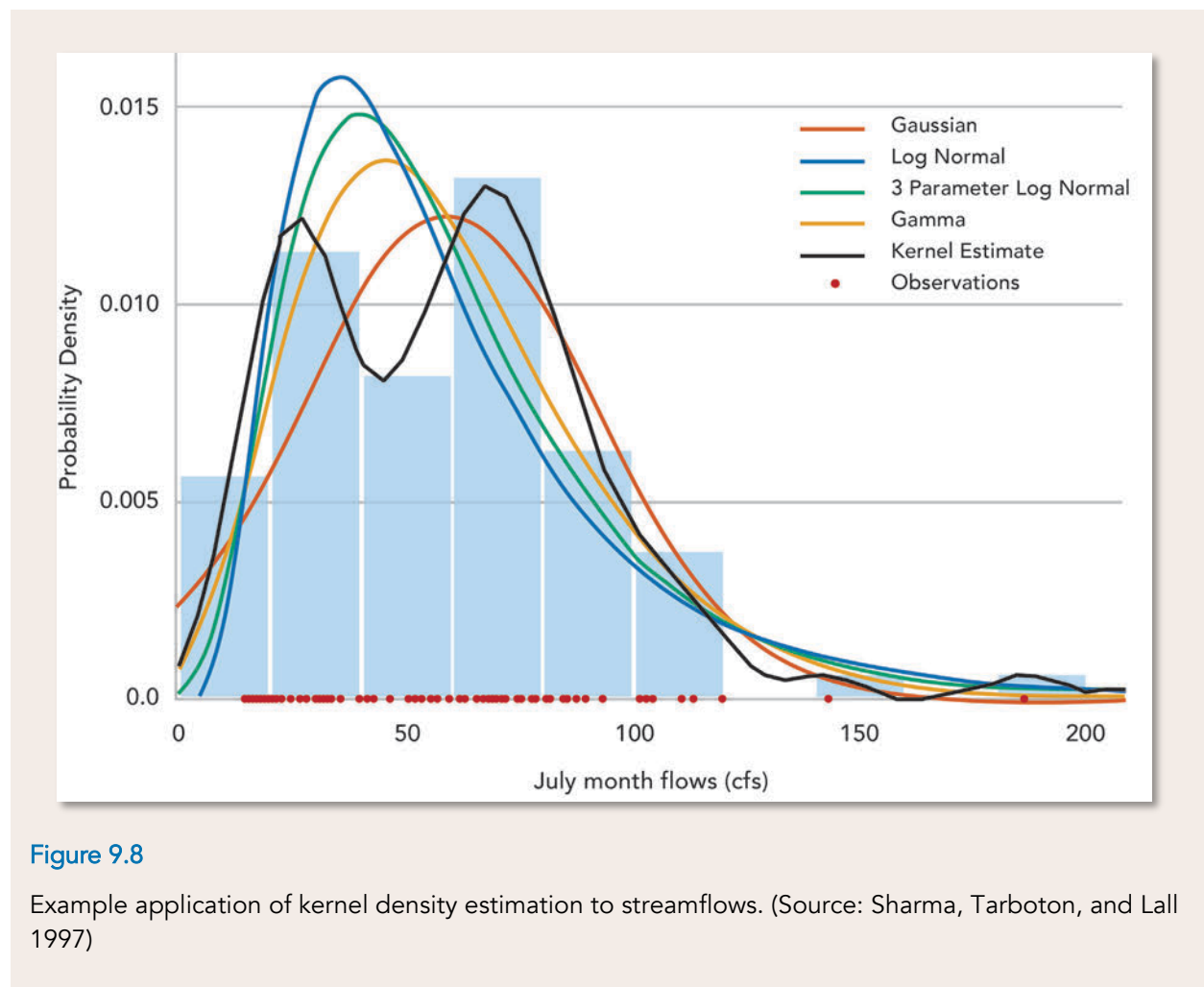
As mentioned above, nonparametric methods rely on empirical data, i.e., the observed hydrology, more directly, rather than fitting the observations to a theoretical PDF and then generating stochastic flows from that PDF. All of the nonparametric methods described here rely on resampling the historical record in some way. Research efforts have shifted to nonparametric approaches for a number of reasons, but primarily because the true form of the distribution of the population of streamflows is unknown, and it is therefore possible that the probability distribution that best fits the observations (i.e., a sample from the population) is not the correct one for the population. Lall (1995) explains the issue:

Usually, the hydrologist has little physical or theoretical guidance as to the specific form of the target function. The traditional exercises amount to choosing between a small set of prescribed curves to fit the data at hand. What is one to do when the naked eye discerns structure in the data, and yet none of the usual candidates fit well? How does one choose between two models that fit equally well in terms of a global measure (e.g., likelihood, or sum of squared residuals), are parsimonious, and yet differ markedly in the details of the fit?...Questions like these invariably steer an investigator into the realm of nonparametric function estimation or "smoothing."

At least two nonparametric methods, kernel density estimation and nearest neighbor density estimation, have been used in studies that have generated stochastic Colorado River streamflows. The two methods are briefly described here.

Unlike parametric methods, kernel methods estimate the overall form of the observations by analyzing smaller intervals, or bandwidths, of the data. The bandwidths are analogous to the bins in a histogram, but instead of estimating a uniform frequency for all values within a bandwidth, the frequency, or density, at each observation point is weighted based on its distance from the center of the bandwidth. In parametric methods, the overall density estimate is made based on the parameters of the entire set of observations. In the kernel method, observations outside each bandwidth have no influence on the density estimate for observations within the bandwidth. The bandwidths are advanced, like a moving average, through all of the observations. The resulting set of local density estimates are aggregated to produce an overall, empirical density function for the entire observational dataset. The empirical density function looks like a smoothed histogram—the larger the bandwidth, the smoother the overall density function, and vice versa. Figure 9.8 illustrates an example application of kernel density estimation to July monthly flows on the Beaver

River in Utah. It offers a graphic comparison of the parametric fits of normal (Gaussian), lognormal and 3-parameter lognormal PDFs to the nonparametric, empirical, kernel density estimate. Only the empirical density estimate captures the bimodal nature of the observations. In the kernel method, the empirical density function becomes the basis for generating stochastic streamflow traces (Lall 1995; Sharma, Tarboton, and Lall 1997; Breheny 2012).



Tarboton, Sharma, and Lall (1998) used kernel density estimation methods in their study of streamflow disaggregation. They observed that the technique is better than parametric techniques at capturing the wet-year vs. dry-year effects on seasonal variability. The primary shortcoming of the method is that it is computationally intensive, with the computational load driven by the size of the matrix resulting from the bandwidth length and the number of parameters used to define the local density estimates. Sharma, Tarboton, and Lall (1997) identify the potential for the method to produce negative flow values.

Prairie et al. (2007) and Nowak et al. (2010) also took nonparametric approaches to disaggregating streamflow. Prairie et al. (2007) disaggregated annual streamflows to monthly flows and Nowak et al. (2010) disaggregated annual streamflows into daily flows and further disaggregated those daily flows spatially to three locations. The methods these authors used for both stochastic streamflow generation and disaggregation were K-NN, or nearest neighbor, methods.

Nearest neighbor methods, pioneered by Lall and Sharma (1996) for application to hydrologic time series, also calculate local density estimates rather than relying on an assumed PDF for the entire set of observations. The term “nearest neighbors” refers to observations that are closest in Euclidean space, i.e., the closest points on a graph of observations vs. frequency or vs. other observations. The local density estimates are based on weighted averages of the K (number of) nearest neighbors to the individual observed flow values, with nearer neighbors being given a greater weight than more distant neighbors. The original K-NN approach resulted in generated values that were sampled from the historical data directly and thus did not introduce new streamflow values, though it did produce new sequences (Prairie et al. 2006). The K-NN method offered by Lall and Sharma (1996) was modified by Prairie et al. (2006) to resample the residuals from local regressions on sets of nearest neighbors and add those residuals to the local means, thereby producing potentially novel streamflow values.

Sharifazari and Araghinejad (2015) extended the modified K-NN model of Prairie et al. (2006) to capture the temporal and spatial streamflow dependence in the Sirwan River Basin in Iran. They also demonstrated a method to shift the generated flows lower or higher by biasing the residuals sampled in the method. According to the authors, this shift could be applicable to generating climate change-informed traces.

Applying paleohydrology, Prairie et al. (2008) took advantage of the most salient features of the reconstructed tree-ring record, i.e., the hydrologic state (wet or dry) and duration, to guide K-NN resampling from the historical, observed record. This effort generated streamflow traces that both preserved the range of flow magnitudes seen in the historical record and provided novel streamflow sequences. This study is described in more detail in Chapter 10.

More recently, and also taking advantage of the tree-ring record, Erkyihun et al. (2016) applied K-NN methods in a study using low-frequency climate signals to generate annual flows at Lees Ferry. The authors discerned climate signals in the reconstructed tree-ring streamflow record that are attributed to the Pacific Decadal Oscillation and Atlantic Multi-decadal Oscillation climate indices. They used K-NN methods to generate annual

flows at Lees Ferry conditioned on those signals. An advantage of using the climate signal is that autocorrelations do not have to be explicitly specified in the annual streamflow generation model—they are implicit in the climate signals.

Parametric approaches to hydroclimatic non-stationarity were described above. Nonparametric approaches have focused primarily on climatic data time series rather than streamflow (Vogel 2017).

Limitations

Nonparametric methods, because they resample from the historical record, are heavily dependent on the length of that record and the variability and range of values therein. The K-NN method depends on a sample size large enough to contain sufficient nearest neighbors to produce a meaningful analysis (Lall and Sharma 1996; Prairie et al. 2006). Prairie et al. (2006) also commented that K-NN did not capture interannual variability well.

Nonparametric methods applied to monthly time steps have difficulty with continuity in the transitions from the last month of one year to the first month of the following year (Prairie et al. 2007). Finally, kernel-based methods require disaggregation techniques that are “inefficient and cumbersome” (Prairie et al. 2007; see also Tarboton, Sharma, and Lall 1998, and Nowak et al. 2010).

Comparisons to ISM

Few formal comparisons have been made between ISM and nonparametric methods. Prairie et al. (2006) found that the modified K-NN method performed better than ISM at capturing features of the monthly flows, though the comparison was somewhat hampered by the relatively short traces produced by ISM. Also, nonparametric stochastic methods, like parametric methods, generate streamflows probabilistically, and therefore are more amenable to probabilistic interpretation.

Hybrid stochastic methods

There have been some efforts to combine parametric and nonparametric approaches to address the limitations of both types of methods in stochastic streamflow generation. These hybrid, or semi-parametric, methods usually apply the parametric and nonparametric methods during different steps of trace generation. Srinivas and Srinivasan (2005) and Herman et al. (2016) both used parametric methods to pre-standardize observations and then used nonparametric resampling methods to generate streamflow traces.

Other stochastic methods

More recent research on stochastic streamflow generation has applied “copulas” or multivariate PDFs that capture the dependencies between variables. Copula methods can be either parametric or nonparametric (Lee and Salas 2011; Hao and Singh 2012; Gold 2017). Hao and Singh (2012) used a copula method to develop a joint probability distribution for monthly Colorado River flows at Lees Ferry. They generated stochastic streamflow traces that simulate the temporal dependence between adjoining months with joint distribution functions for each pair of months.

Another recently developed approach is the multi-site multi-season maximum entropy bootstrap (M3EB) method (Srivastav and Simonovic 2014). The authors present a case study using four sites in the Upper Colorado River Basin: Colorado River near Cisco, Utah; Green River at Green River, Utah; San Juan River near Bluff, Utah; and Colorado River at Lees Ferry, Arizona. The method preserves the statistical characteristics and the temporal and spatial dependence structure of the historical data. The authors state that this method is capable of modeling both non-stationarity and seasonality.

A selected list of published applications of stochastic methods to generate streamflow traces from the historical hydrology in the Colorado River Basin is provided in Table 9.3. The list includes both parametric and nonparametric approaches. It does not include the many studies of stochastic approaches that have been applied to meteorological variables in the basin, or studies that do not use the historical hydrology directly, such as paleohydrology studies and climate change-informed hydrology studies. Those studies are described in Chapters 10 and 11, respectively.

Table 9.3

Selected studies in which stochastic methods were used to generate hydrologic traces from Colorado River Basin historical hydrology.

Type	Method or model name	Application	Reference
Parametric	LAST	Generated monthly streamflow traces for the Colorado River at Lees Ferry, with each month having a unique PDF transformation	Frevert and Cheney 1988
Parametric	SPIGOT	Generated annual, autoregressive, lag-one (AR-1) lognormal streamflow traces for the Colorado River at Lees Ferry	Kendall and Dracup 1991*
Parametric	SPIGOT	Used SPIGOT to disaggregate annual flows from tree ring reconstructions of the Colorado River at Lees Ferry in order to generate monthly streamflow traces for 29 locations in the Colorado River Basin	Tarboton 1994, 1995
Parametric	LAST	Generated monthly streamflow traces for 23 locations in the Colorado River Basin	Ouarda, Labadie, and Fontane 1997*
Nonparametric	Kernel-based technique	Compared SPIGOT vs kernel-based disaggregation methods for stochastic flows on the San Juan River	Tarboton, Sharma, and Lall 1998
Nonparametric	Modified K-NN	Compared monthly generated flows using modified K-NN to ISM flows and to parametrically generated (SAMS) flows at Lees Ferry	Prairie et al. 2006*
Parametric	LAST, SAMS and SPIGOT	Generated monthly streamflow traces for 29 locations in the Colorado River Basin from both spatial and temporal disaggregation of annual flows	Lee et al. 2007
Nonparametric	Modified K-NN	Disaggregated annual stochastic flows into monthly flows at four sites in the Upper Colorado Basin: Colorado River near Cisco, Utah; Green River at Green River, Utah; San Juan River near Bluff, Utah; and Colorado River at Lees Ferry, Arizona	Prairie et al. 2007
Nonparametric	K-NN	Generated annual streamflow traces at Lees Ferry by using the streamflow states from the tree-ring record to guide K-NN resampling from the historical record	Prairie et al. 2008

Type	Method or model name	Application	Reference
Nonparametric	K-NN	Generated daily streamflow traces for 3 locations on the San Juan River by using K-NN methods to disaggregate annual flows in both space and time	Nowak et al. 2010
Parametric	Copula	Generated monthly flows at Lees Ferry from joint probability distributions for each pair of months	Hao and Singh 2012
Nonparametric	M3EB	Generated monthly flows at Colorado River near Cisco, Utah; Green River at Green River, Utah; San Juan River near Bluff, Utah; and Colorado River at Lees Ferry, Arizona	Srivastav and Simonovic 2014
Nonparametric	WKNN	Derived low frequency climate signals from tree-ring flows and used K-NN to resample the historic observations to generate annual flows at Lees Ferry	Erkyihun et al. 2016

*Performed comparisons to ISM

9.4 Challenges and opportunities

This chapter has focused on the state of the science of applications of the observed, historical time series for long-term planning studies in the Colorado River Basin. All of the studies cited in this chapter use the historical time series, or characteristics of it, as inputs to, or benchmarks for, the various methods to generate synthetic streamflow traces. However, as described throughout the chapter, there are challenges to synthesizing streamflow traces from the historical record. Some of the higher level challenges, and opportunities to address them, are discussed below.

Challenge

Identifying the most appropriate method of incorporating historical hydrology in long-term planning in the Colorado River Basin is a key challenge. The full, observed historical record, especially when used with ISM, likely does not represent future hydrologic risk, but it is challenging to completely replace it because there is no clear best alternative. While Reclamation's use of a segment of the observed hydrology (the Stress Test) attempts to create a more realistic picture of risk, there is little guidance on which segments are most appropriate, and a shorter record reduces the range of hydrologic conditions available. Beyond ISM, there is much research but little consensus on alternative approaches to generating synthetic streamflow traces.

Opportunity

- One approach, informally suggested by Tarboton (pers. comm.), is that new streamflow generation models be tested against a comprehensive set of statistics. Extending that suggestion somewhat, a matrix could be established by Reclamation and basin stakeholders that identifies the most important features of synthetic traces and uses that matrix to guide research into new methods or to assess existing methods. Features in the matrix might include fidelity to particular historical statistics, ability to generate particular time steps, ability to simulate non-stationarity, ability to represent uncertainty, ease of implementation, ease of understanding, and robustness of inferences.

Challenge

One of the primary challenges facing water resources researchers and planners in applying the basin's historical time series is how to use it to generate streamflow traces that allow study of the non-stationary hydroclimate.

Opportunities

- Explore performing diagnostics on the parameters used in parametric stochastic streamflow studies in the Colorado River Basin to assess the dependencies between and among parameters and to assess the complexities involved in incorporating non-stationarity into them.
- Techniques for generating long-term streamflow sequences that blend historical observed hydrology with paleohydrology or climate change-informed hydrology (or both) offer substantial promise. The paleo record offers extremes, durations, and frequencies not seen in the observed record, and the climate change-informed hydrologies offer potentially altered climate patterns and regional shifts that are absent or undetectable from the observed and paleo records. For more information about these opportunities, see Chapters 10 (Paleohydrology) and 11 (Climate change-informed Hydrology).
- This chapter has focused on research into streamflow synthesis but there is a wealth of information about methods applied to synthesize time series for other hydrometeorological variables. A potentially useful effort might be to review approaches to other variables, and even other disciplines, for techniques that could be translated into streamflow synthesis techniques.



Chapter 10

Paleohydrology

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383. Western Water Assessment, University of
Colorado Boulder.

Key points

- Tree-ring reconstructions of Colorado River streamflow extend the observed natural flow record up to 1200 years into the past and document a broader range of hydrologic variability and extremes than are contained in the observed records.
- Most critically, several paleodroughts prior to 1900 were more severe and sustained than the worst-case droughts since 1900.
- These “megadroughts” could recur in the future due to natural climate variability alone, but their recurrence risk is much increased by anthropogenic warming.
- The century-scale mean and variability of Colorado River Basin hydroclimate has not been stationary over time.
- The early 20th century high-flow years (1905–1930) may have been the wettest multi-decadal period in 500–1000 years.
- Methodological choices in the handling of the tree-ring data can influence the reconstructed flow values and metrics, such as the duration of droughts.
- Planning hydrologies derived from tree-ring paleohydrology can provide plausible stress tests that are more extreme than the observed hydrology, and have been used for that purpose in several recent planning studies in the basin.

10.1 Introduction to tree-ring reconstructions of streamflow

As outlined in the Volume IV introduction, water resources planning has traditionally been based on observed records of climate and hydrology, which extend up to 120 years into the past, at best. Through the 20th century, the assumption that future Colorado River Basin supply could be represented in planning by the observed hydrology alone went largely untested. However, by the mid-2000s, with the demands for basin water approaching or exceeding supply, rapid declines in reservoir levels due to severe drought, and the growing realization that climate change could result in reduced flows, water agencies increasingly looked to tree-ring reconstructions of paleohydrology for additional perspective on water supply risk.

Tree-ring reconstructions of streamflow are based on moisture-limited trees that provide a proxy record of hydroclimatic variability. The annual ring widths in these trees correspond primarily to variations in moisture, particularly if they are growing on open, south-facing slopes with thin soils, where competition from other trees is limited and site conditions are particularly stressful. In these sites, tree-ring widths reflect a high degree of year-to-year moisture variability (Fritts 1976). While reconstructions of precipitation rely on a direct relationship between moisture and tree

growth, the relationship between tree growth and streamflow is less direct (Meko, Stockton, and Boggess 1995). In the case of the upper Colorado River Basin, water year streamflow and annual ring widths are both the result of the cumulative influence of hydroclimate conditions over the course of the water year. In both cases, cool season precipitation is the most important factor, leading to the snowpack that runs off into the river while conditioning spring soil moisture that is critical for tree growth (Woodhouse and Pederson 2018). Because of this relationship, trees most useful for streamflow reconstruction are not found in the floodplain, but instead are growing on uplands in the same “climate-shed” that produces the runoff for annual flow.

In the Colorado River Basin region, the low- to mid-elevation conifers (pinyon pine, ponderosa pine, and Douglas fir) are the species most sensitive to hydroclimate (Schulman 1956) and are targeted for collection. Once a site with the appropriate characteristics, tree species, and evidence of long-lived trees is located, approximately 20 living trees are sampled with an increment borer. Cross sections from dead trees, which can be preserved on the landscape for hundreds of years, may be cut with a chainsaw.

Back at the laboratory, each sample is dated to the exact calendar year using a pattern-matching technique called crossdating (Fritts 1976), which also enables wood from dead trees to be dated if it overlaps in time with the living trees. Once all samples are dated, they are measured using a sliding-stage micrometer to the precision of 0.001 mm. The time series of measurements typically show a declining trend over time in ring-width due to age and tree geometry, so the series are detrended to remove this effect, which is unrelated, for the most part, to climate (Cook and Kairiūkštis 1990). Two different “flavors” of detrended series are generated: one in which the low-order persistence in growth that is largely attributable to tree biology (year-to-year carbohydrate storage) is removed, resulting in so-called “residual” chronologies; and one in which that persistence is retained, resulting in “standard” chronologies. Measurements from all samples at a site are robustly averaged into a site tree-ring chronology, or time series, which is the basic unit used in the reconstruction process (Woodhouse et al. 2016).

Reconstructions of climate are developed by calibrating the annual tree-ring chronologies with a record of observed climate or hydrology over a common period of years. The calibration process usually employs some type of multiple linear regression, with tree-ring chronologies as the predictors and the observed climate or streamflow record as the predictand. There are many statistical approaches that may be taken for model calibration, but the two most common approaches are stepwise regression using individual chronologies as predictors, and principal

components regression, which reduces a set of chronologies to a smaller set of time series uncorrelated with each other that expresses the underlying principal modes of tree-growth variability, which are then used as the predictors.

Model validation is a key step in the reconstruction process. Validation involves withholding some subset of data, refitting the model on the remaining data, and assessing the model fit to the withheld data. This can be accomplished through cross-validation in which values from one or more years are iteratively removed and replaced until a complete validation time series has been generated (Michaelsen 1987; Woodhouse and Pederson 2018). Alternatively, a split-sample validation approach is used in which a portion of the calibration time series (typically at least 20 years) not included in the model calibration is used solely for model validation (Fritts, Guiot, and Gordon 1990).

The skill of the calibration model in estimating the observed values is assessed with statistics that include the explained variance (R^2) and standard error (SE). These statistics are compared to those generated from the validation data and include the reduction-of-error (RE) statistic (Fritts, Guiot, and Gordon 1990), which measures the ability of the reconstruction model to outperform a null model (e.g., the mean of the observed streamflows during the calibration period) and yields the root mean squared error (RMSE) of the validation data. Other visual and statistical comparisons are often performed as well.

10.2 Upper Colorado River Basin flow reconstructions

History of Upper Basin streamflow reconstructions

Edmund Schulman, one of the pioneers of tree-ring science, was the first to investigate the use of moisture-sensitive conifer tree rings to document past precipitation and streamflow in the Colorado River Basin (Figure 10.1). While Schulman's work in the 1940s was based on relatively few tree-ring samples and predated the availability of computer-aided statistical modeling, his proxy record of streamflow captured the main features of later reconstructions that used far more tree-ring data and modern statistical calibration approaches (Schulman 1945). Schulman's work included a report to the Los Angeles Department of Power and Light ("A Tree-Ring History of the Runoff of the Colorado River 1366–1941"), which indicates the interest of water-management agencies in tree-ring paleohydrology from its earliest days.

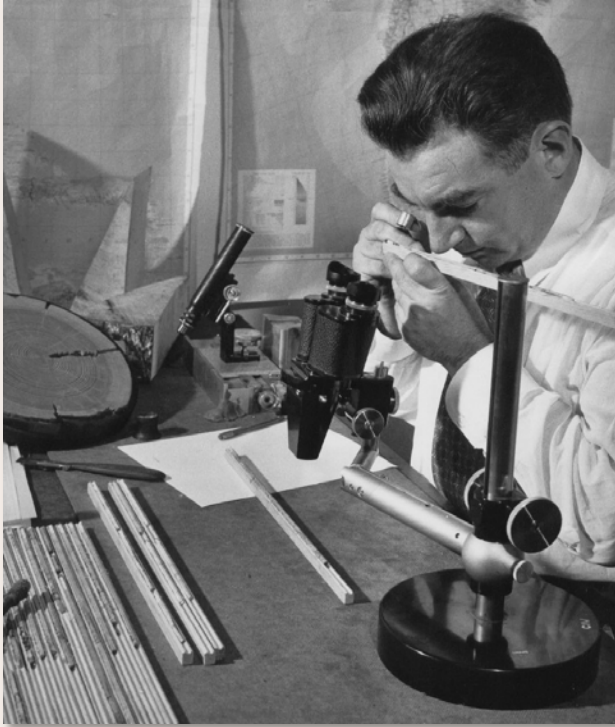


Figure 10.1

Edmund Schulman developed the first tree-ring proxy record for Colorado River streamflow in the early 1940s. That record, which extended back to the 1300s, captured many of the major droughts and wet periods seen in more recent Colorado River streamflow reconstructions. (Source: Laboratory of Tree-Ring Research, University of Arizona)

The first modern calibrated streamflow reconstructions for the Colorado River were developed by Stockton and Jacoby (1976), building on the preliminary work of Stockton (1975). Stockton and Jacoby developed multiple reconstruction models using two subsets of tree-ring chronologies and several different naturalized flow records for model calibration. Their final, published, Lees Ferry reconstruction was an average of the two models they deemed most reliable and extended from 1520–1961, with a long-term mean flow of 13.4 maf, explaining 87% of the variance in the 1914–1961 observed flow record (Stockton and Jacoby 1976).

Two additional Lees Ferry reconstructions were generated in the 1980s and 1990s based on the same or similar sets of tree-ring chronologies as Stockton and Jacoby, with models that used different types of multiple linear regression (Table 10.1): Michaelsen et al. (1990), in research undertaken for the California Department of Water Resources, and Hidalgo et al. (2000). The Hidalgo et al. long-term reconstructed mean flow of 13.0 maf is lower than any other reconstruction, likely as a result of their particular methodology, as discussed below.

Table 10.1

Summary of statistical characteristics of published Colorado River at Lees Ferry reconstructions, updating Table U-6 in Reclamation (2007)

Reconstruction	Calibration years	Source of Observed Natural Flow Data	Chronology Type	Regression approach	Variance explained (R ²)	Reconstruction years	1568–1961 mean (maf)
Stockton and Jacoby (1976)	a. 1899–1961	Hely, 1969	standard	PCA with lagged predictors	0.75	1512–1961	14.2
	b. 1914–1961	Hely, 1969	standard	"	0.78	1512–1961	13.9
	c. 1914–1961	UCRSFIG, 1971	standard	"	0.87	1511–1961	13.0
	Average of b and c					1520–1961	13.4
Michaelsen et al. (1990)	1906–1962	Simulated flows	residual	Best subsets	0.83	1568–1962	13.8
Hidalgo et al. (2000)	1914–1962	USBR (see ref)	standard	Alternative PCA with lagged predictors	0.82	1493–1962	13.0
Woodhouse et al. (2006)							
(Lees–A)	1906–1995	USBR	residual	Stepwise	0.81	1490–1997	14.7
(Lees–B)	1906–1995	"	standard	Stepwise	0.84	1490–1997	14.5
(Lees–C)	1906–1995	"	residual	PCA	0.72	1490–1997	14.6
(Lees–D)	1906–1995	"	standard	PCA	0.77	1490–1997	14.1
Meko et al. (2007) (nested model)	1906–2004	USBR	residual	2-step regression with PCA, nested models	0.76	762–2005	14.7
Meko et al. (2017)							
(most skillful)	1906–2015	USBR	standard	Interpolation from regression scatterplot, nested models	0.81	1416–2015	14.2
(longest)	1906–2014	USBR	standard	Same as above but no nesting	0.58	1116–2014	14.2
Gangopadhyay et al. (2009)	1922–1997	USBR	standard	K-Nearest Neighbor (K-NN)	0.76	1400–1905	‡
Gangopadhyay et al. (2015)*	1910–1997	Simulated flows	standard	K-Nearest Neighbor (K-NN)	r = 0.63 (med)	1404–1905	‡

Reconstruction	Calibration years	Source of Observed Natural Flow Data	Chronology Type	Regression approach	Variance explained (R ²)	Reconstruction years	1568–1961 mean (maf)
Bracken et al. (2016) [†]	1952–1997	USBR	residual	Nonhomogeneous Hidden Markov Chains (NHMC)	r = 0.91	1473–1906	‡

*Includes additional reconstructions for 5 tributary gages
[†]Includes additional reconstructions for 19 main stem and tributary gages
[‡]The non-parametric models do not produce reconstructed flows for the post-1905 period, so comparisons over this full period are not possible

In the late 1990s and early 2000s, major efforts were undertaken to update and expand the tree-ring chronologies collected in the upper Colorado River Basin and adjacent areas. These new chronologies enabled the next generation of Colorado River reconstructions, which took advantage of the longer calibration period. Because the calibration period was extended to include an additional 33 to 53 years (the latter nearly doubling the calibration period of pre-2006 reconstructions), these reconstructions are considered more robust. This additional credibility is due to both the extended length of the calibration period and the broader range of variability for model calibration. The first of these new chronologies expanded the Lees Ferry streamflow reconstruction start and end dates to 1490–1997/1998 (Woodhouse, Gray, and Meko 2006). Under that effort, four different reconstruction models were developed to test the sensitivity of reconstruction results to 1) autocorrelation in the tree-ring data and 2) the multiple linear regression approach used.

On the heels of that work, Meko et al. (2007) developed a subset of tree-ring chronologies that incorporated remnant material from dead trees to extend the tree-ring records back even further in time, along with updated chronologies, to generate a reconstruction of streamflow from 762–2005. This extended reconstruction revealed a much larger range of variability, including a much longer period of sustained drought in the 12th century, than had been documented in the shorter reconstructions. This reconstruction was largely based on the same set of chronologies as used in Woodhouse et al. (2006) back to the 1400s: To deploy the largest set of available chronologies back in time, Meko et al. (2007) used four nested sub-period reconstruction models. While the explained variance for the model that covers the longest sub-period (1365–2002) is very similar to explained variance in the models for Woodhouse et al. (2006), the model covering the earliest period, extending back to 762, is less skillful (Table 10.1).

Figure 10.2 shows the locations of streamflow reconstructions in the Colorado River Basin.

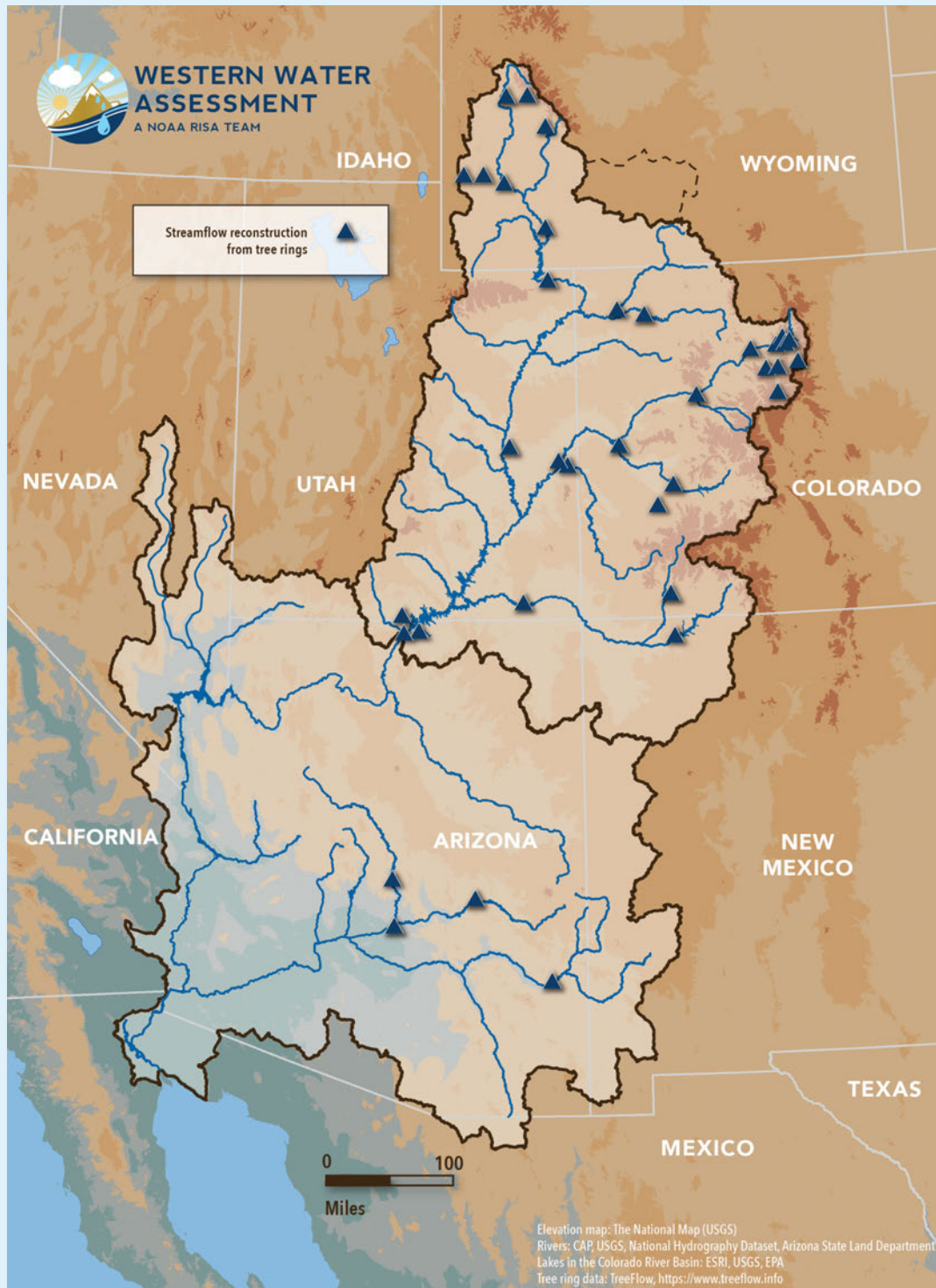


Figure 10.2

Locations for which naturalized annual streamflows have been reconstructed using tree-ring records, with the reconstruction data available from the TreeFlow website. The lengths of the reconstructions range from 385 years to 1244 years. Three different reconstructions of the Colorado River at Lees Ferry are available from TreeFlow; see the text for more information about these and other Lees Ferry reconstructions. (Source: TreeFlow; <https://www.treeflow.info>)

Most recently, the California Department of Water Resources funded Meko and Woodhouse to update a subset of the Upper Basin tree-ring chronologies in order to include the most recent drought years in the streamflow calibration series (Meko, Woodhouse, and Bigio 2017). Under that effort, two Lees Ferry reconstructions were generated: a shorter, more skillful reconstruction (1416–2015; $R^2 = 0.81$) and a longer but less skillful reconstruction (1116–2015; $R^2 = 0.58$).

A comparison of all of the Lees Ferry reconstructions described above is shown in Figure 10.3 for the years they have in common, 1568–1961. Reconstructions have been smoothed with a 20-year moving average (plotted on the last year) to facilitate visual comparison. In general, the reconstructions are very similar in their depictions of the timing of shifts between high and low flow periods. The period in which reconstructions are perhaps most different is the wet period in the early 1600s, with the Michaelsen et al. (1990) reconstruction showing flows barely above their long-term average, while the more recent reconstructions show the highest values (Meko et al. 2007; Meko, Woodhouse, and Bigio 2017; Woodhouse, Gray, and Meko 2006). This suggests the influence of the larger set of tree-ring chronologies in the Upper Basin starting with the 2006–07 reconstructions.

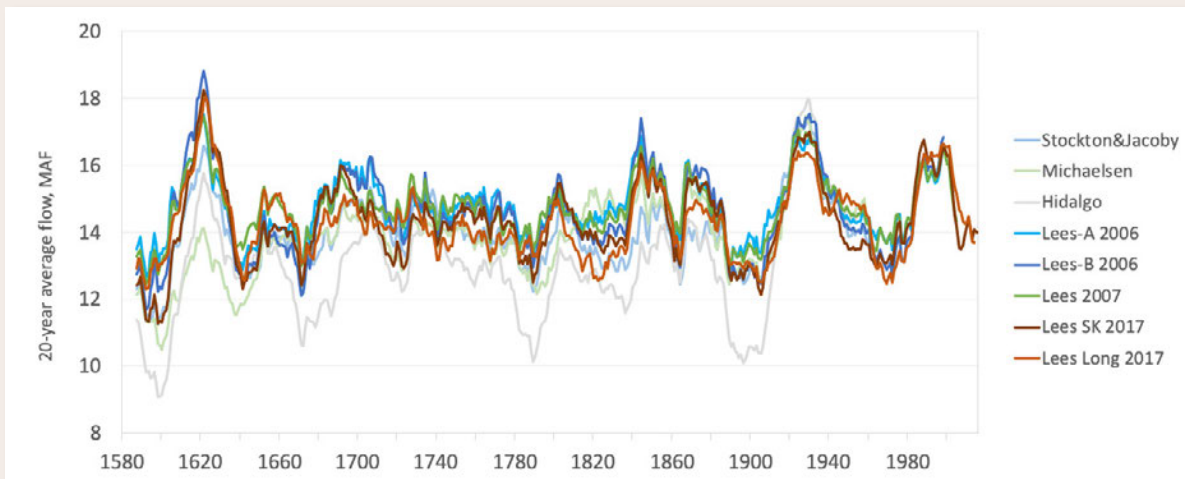


Figure 10.3

Comparison of eight tree-ring reconstructions of the Colorado River at Lees Ferry, showing the similarities in the timing of decadal-scale dry and wet periods. The most recent reconstructions (published after 2005) are emphasized with darker colors due to their more robust tree-ring datasets and longer calibration periods than earlier reconstructions. All series are smoothed with a 20-year moving average and plotted on the last year of the 20-year period. (Data: Treeflow (<https://treeflow.info>) and C. Woodhouse)

The Hidalgo et al. (2000) reconstruction clearly differs the most from the others, showing much lower flows during drought periods than the other reconstructions. That reconstruction used a set of tree-ring chronologies similar to Stockton and Jacoby, but with a different PCA regression approach that apparently enhances the year-to-year persistence of flow anomalies, and thus the magnitudes of extended low-flow periods. An independent estimate of gaged flows during the late 1800s drought suggests that the Hidalgo et al. reconstructed flows during that period—and by extension, previous drought periods—are implausibly low. In the 1920s, a USGS hydrologist used observed stage height of the Colorado at Yuma to estimate annual flows at Yuma back to 1878; converting these to natural flows at Lees Ferry gives an average of 13.5 maf for the period 1886-1905 (Kuhn and Fleck 2019). The Hidalgo et al. reconstruction indicates only 10.4 maf for this same period, while the other seven reconstructions are in the range of 12.1-13.4 maf.

In addition to these regression-based (i.e., parametric) reconstructions of the Colorado River at Lees Ferry, reconstructions have been generated using non-parametric statistical approaches. The non-parametric approaches do not assume that the data are normally distributed, and can produce ensembles of reconstructed flow values for each year, expressing the uncertainty in the reconstruction. These non-parametric reconstructions have generally used the same set of tree-ring chronologies developed for Woodhouse et al. (2006) and Meko et al. (2007), along with a few updated chronologies. Gangopadhyay et al. (2009) employed K-nearest neighbor (K-NN) techniques to develop an ensemble of Lees Ferry annual streamflow traces. Bracken et al. (2016) used a hierarchical Bayesian nonhomogeneous hidden Markov model (NHMM) to develop reconstructions for a network of 20 Upper Basin gages, including Lees Ferry. Both sets of reconstructions extend back to the 15th century, with mean explained variance of $R^2 = 0.76$ (Gangopadhyay et al. 2009) and $R^2 = 0.83$ (Bracken, Rajagopalan, and Woodhouse 2016), respectively, indicating overall skill similar to regression-based reconstructions.

The main strength of these approaches over linear regression is their explicit representation of uncertainty with more realistic confidence intervals, and in the case of Bayesian NHMM, the replication of observed spatial relationships among tributary gages. The resulting reconstructions themselves are similar in skill to those produced by regression approaches, and also show similar magnitudes for the extended dry and wet periods, clearly demonstrating the robustness of the overall hydroclimatic signal that emerges from the current set of tree-ring chronologies in this region (Table 10.1).

Most recently, Gangopadhyay et al. (2015) used a water balance model and the set of chronologies that had been used in Gangopadhyay et al. (2009) in

a K-NN approach to generate a suite of hydroclimatic reconstructions, including the Colorado River at Lees Ferry, back to 1404. In that case, the median correlation between the water year streamflow reconstructions (1906–1997) and the observed flow record was $r = 0.63$.

In addition to these reconstructions of the Colorado River at Lees Ferry, water year streamflow has been reconstructed for 30 other main stem and tributary gages throughout the Upper Basin, as well as 4 tributary gages in the Lower Basin, all in the Gila River basin. These reconstructions are listed in the [TreeFlow web resource](#) (CLIMAS and WWA n.d.), with links to the data and metadata.

Comparison of recent Lees Ferry reconstructions

The Lees Ferry streamflow reconstructions generated since 2006 (Woodhouse, Gray, and Meko 2006; Meko et al. 2007; Meko, Woodhouse, and Bigio 2017) have used the same or very similar sets of tree-ring chronologies as potential predictors of streamflow. Consequently, these regression-based reconstructions are quite similar (average correlation between reconstructions over common years: $r = 0.88$, ranging from $r = 0.76$ to $r = 0.96$) but with some key differences that highlight the impact of choices made when reconstruction models were developed. These differences are mostly due to treatment of the autocorrelation that is found in the ‘raw’ tree-ring data and type of multiple linear regression modeling used.

Most obvious are the differences in explained variance (Table 10.1). The reconstructions, or portions of reconstructions, that extend farthest back in time have the lowest skill, as they are based on a much-reduced subset of the tree-ring chronologies—for example, the Meko et al. (2007) model that starts in 762, and the Meko et al. (2017) longest reconstruction. Putting these two aside, the explained variance of the other reconstructions ranges from $R^2 = 0.77$ to $R^2 = 0.84$.

Since the reconstructions listed in Table 10.1 used different calibration periods and different natural flow records for calibration, a more uniform comparison of the reconstructions can be made based on their correlations with the latest version of the Lees Ferry estimated natural flows (as of September 2018) over a common interval of time (1906–1997). In this comparison, the reconstructions with the highest correlations with flow are non-PCA regression reconstructions from Woodhouse et al. (2006) (Lees B, standard chronologies, $r = 0.916$) and Meko et al. (2017) (shorter more skillful version, $r = 0.914$), followed by the Lees A (residual chronologies, $r = 0.895$). The two that are most skillful are generated from standard chronologies, i.e., those with biological persistence retained, so that the series contain statistically significant lag-1 autocorrelations.

Treeflow



Link:
<https://www.treeflow.info/>

Going beyond the strength of the relationships between reconstructed and estimated natural flows, an examination of basic statistical characteristics such as the minimum, maximum, and range coincides with what might be expected, given differences in explained variance. In other cases, the results provide some insights into modeling choices. Perhaps the most revealing comparison is with the lag-1 autocorrelation values, i.e., year-to-year persistence. In the observed flow record, this value is $r = 0.235$ (significant at $p = 0.02$). The reconstructions based on residual chronologies, in which biological persistence was removed (Lees A and Lees C), as expected show autocorrelation values over the calibration period of $r \approx 0$. The two Meko et al. (2017) reconstructions have somewhat higher persistence ($r = 0.338$ and $r = 0.379$) than the observed natural flows, while Lees B ($r = 0.221$) and Lees 2007 ($r = 0.243$) appear to be the closest match to the persistence in the observed natural flows. Higher autocorrelation values will result in longer periods of drought being seen in the reconstructed flows. For example, the Meko et al. (2017) most-skillful reconstruction contains two 10-year, one 11-year, and one 15-year drought over the years 1416–2005, while the longest drought shown in Lees 2007 during this same period lasted only 8 years. (Drought is defined here as consecutive years below the observed average.)

There is no perfect reconstruction and trade-offs are unavoidable, the most obvious being between skill and length. But this comparison does suggest that the use of standard chronologies preserves important autocorrelation in the system, though more work is needed to determine what modeling choices beyond the type of chronology may better replicate the autocorrelation in the observed hydrology. Given this, any of the following recent reconstructions of Lees Ferry flow would be appropriate for water supply analysis and as inputs to system modeling; the fact that they show differences between them is reflective of the uncertainties inherent in any one reconstruction, as outlined in the next section.

- Lees B (Connie A. Woodhouse, Gray, and Meko 2006)
- Lees 2007 (Meko et al. 2007)
- Lees 2017, either model (Meko, Woodhouse, and Bigio 2017)
- Gangopadhyay et al. K-NN (Gangopadhyay et al. 2009)
- Bracken et al. NHMM (Bracken, Rajagopalan, and Woodhouse 2016)

Of these reconstructions, Lees 2007 has seen the most use in recent water-supply analyses for the basin, including those supporting the 2007 Interim Guidelines (Appendix N; Reclamation 2007b) and in the Basin Study (Reclamation 2012b). Lees-B was used in the initial analyses performed for the Draft EIS for the 2007 Interim Guidelines.



Megadroughts: Past occurrences and future risk

The term *megadrought* was first used by Woodhouse and Overpeck (1998) to refer to droughts, as documented by paleoclimatic data, that lasted longer than any that occurred in the period of instrumental data across the central and western U.S. The term was then highlighted in Stahle et al.'s paper, "Tree-Ring Data Document 16th Century Megadrought of North America" (Stahle et al. 2000), and has been widely used since.

A megadrought is most often defined as a drought over a given area or for a spatial extent that is as severe as, but longer than, any in the 20th century (e.g., Cook 2004; Ault and St. George 2018). The definition may include a more specific interval, such as 20–40 years (Herweijer et al. 2007), longer than 35 years (Ault and St. George 2018), or include any droughts that exceed both the duration and severity of 20th century droughts (Stahle et al. 2007). While many droughts during the pre-instrumental (pre-1900) period have been identified as megadroughts, the most well-known are those of the medieval period (~850–1300), which extended across western North America, including the Colorado River Basin (Cook 2004; Meko et al. 2007). In the Upper Basin, the most notable megadrought occurred during the mid-1100s, with 13 consecutive years of below-average reconstructed flow at Lees Ferry, and the driest 25-year period (1130–1154), averaging less than 84% of the observed period average flow for 1906–2004 (Meko et al. 2007). Figure 10.4 shows the mid-1100s megadrought and three others that occurred between 800 and 1600.

Tropical Pacific sea surface temperature (SST) variability, and specifically, persistent cool anomalies, similar to La Niña events, has been suggested as the primary causal mechanism for the medieval-era megadroughts, with a possible role for SSTs in the Atlantic (Seager et al. 2008). Studies using GCMs that show megadrought behavior in pre-20th century simulations strongly suggest that internal climate variability alone has been responsible for these droughts (Coats et al. 2015). The medieval period of more frequent and persistent droughts does not appear to have been accompanied by similarly persistently cool tropical Pacific SSTs, suggesting a mean shift did not occur over this period, and that other modes of climate variability also played a role (Coats et al. 2016).

What we know about the causes of megadroughts suggests that events like the persistent droughts of the medieval period could occur in the future due to natural climate variability alone. Recurrences of such droughts would produce even lower flows than shown in the reconstructions due to the additional impact of warmer conditions (Woodhouse et al. 2010). For example, Udall and Overpeck (2017) concluded that a recurrence of the lowest 25-year period in the Lees 2007 Colorado River flow reconstruction, which had flows of 84% of average, would, in a warmer future, have flows of 78% of average under a 1°C (1.8°F) warming and 65% of average under a 3°C (5.4°F) warming, assuming a mid-range temperature sensitivity of basin runoff.

A number of studies have employed both paleoclimatic reconstructions of drought and output from multiple global climate models to estimate the risk of drought across the southwestern U.S., including the basin, over the next century. Cook et al. (2015) found that drought risk across the U.S. Southwest and Central Plains is likely to surpass even the driest centuries of the medieval period, under both moderate-emissions (RCP4.5) and high-emissions scenarios (RCP8.5). In the Southwest, the risk of decadal-scale megadrought is estimated to be at least 80%, the risk of a 35-year megadrought from 20-50%, and the risk of a 50-year megadrought under the highest emissions scenario is 5-10% (Ault et al. 2014). The importance of warming temperatures in this region is highlighted by Ault et al. (2016), who found that megadrought risk increased to above 90% by the end of the 21st century, even without changes in precipitation. This importance of warming temperatures with regard to reduction in flow was underscored by the findings of Udall and Overpeck (2017) for the Colorado River.

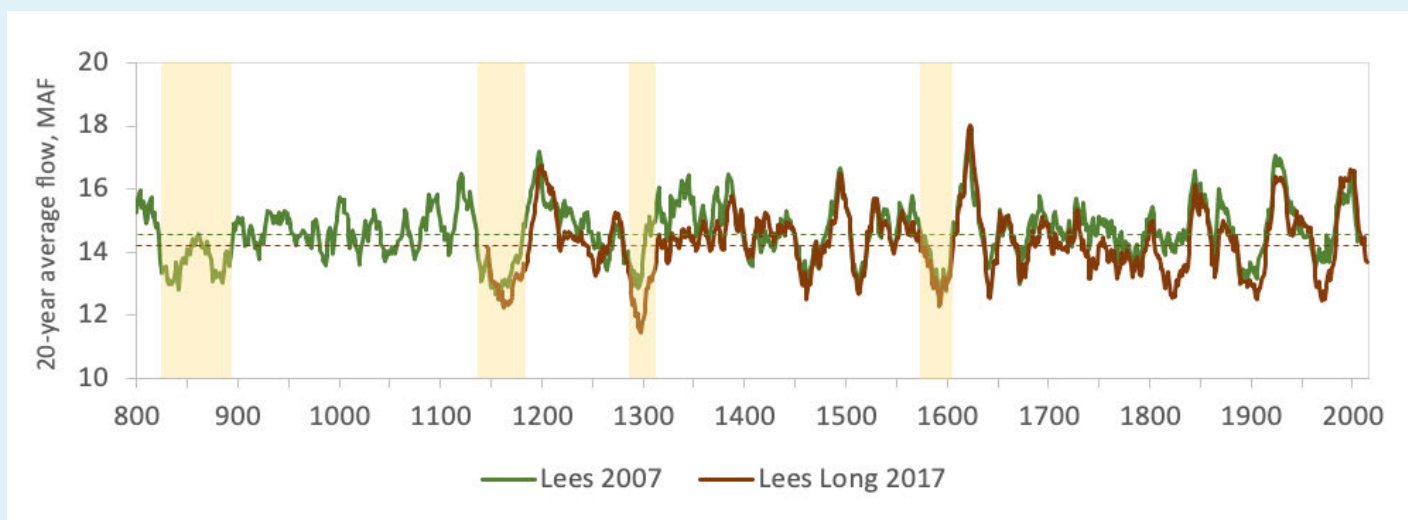


Figure 10.4

Comparison of the reconstructed annual flows, with a 20-year running average, for the Colorado River at Lees Ferry from Meko et al. (2007) ('Lees 2007') and Meko et al. (2017) ('Lees Long 2017'; long version). Four megadroughts are highlighted in yellow, the first three of which occurred during the medieval period: 1) one in the 9th century, 2) one in the 12th century, 3) one in the late 13th and early 14th century, and 4) one in the late 16th century. Other paleoclimate reconstructions indicate that the impacts of these four megadroughts extended throughout much of western North America.

10.3 Sources of uncertainty in tree-ring reconstructions

Because tree rings are imperfect proxies for streamflow, there are inevitable uncertainties in the reconstructions. Additional uncertainties arise from the choices made during the handling of the tree-ring data and the reconstruction model. A more detailed overview of the sources of reconstruction uncertainty can be found in Meko and Woodhouse (2011). The factors that lead to differences and uncertainty include:

- Noise in the trees' recording of hydroclimatic conditions (signal)
- The selection of the tree-ring chronologies to use in the pool of candidate predictors
- The processing of those chronologies (detrending method; residual vs. standard chronology)
- The selection of the naturalized streamflow record used in the calibration
- The length of the calibration period
- The choice of statistical model used for calibration
- The choice of calibration/validation scheme

Metrics of error such as RMSE quantify the uncertainty for an individual reconstruction related to the imperfect calibration fit between the modeled flow and the observed flow, and allow one to construct confidence intervals around the reconstruction. But RMSE and resulting confidence intervals do not capture the uncertainties related to the data handling and modeling choices above. The overall effect of these uncertainties is better illustrated by the differences between the various Lees Ferry reconstructions (Table 10.1, Figure 10.3).

While the Colorado River streamflow reconstructions have some of the most robust calibration/verification statistics of any tree-ring reconstructions of hydroclimate, 20% or more of the variance in the gage record remains unexplained. Linear regression modeling, used for most of the reconstructions in Table 10.1, tends to compress the range of the input data, so that extreme low-flow values are typically overestimated by the model, and extreme high-flow values are typically underestimated. Consequently, the reconstructed values for drought years can be interpreted as conservative estimates of actual streamflows in most cases.

10.4 Value and application of paleohydrology in water supply analyses

Reconstructions of Colorado River streamflow extend the gaged record up to 1200 years into the past and document a broader range of hydrologic variability and extremes than are contained in the relatively short observed

records. They indicate, for example, that drought events far more persistent than any observed over the instrumental period have occurred under natural climate variability alone; that is, without significant human influence on the climate (Meko et al. 2007). The reconstructions also clearly document that the hydroclimate of the basin has been non-stationary; the mean and variability are not constant from one century to the next. While climate change will be a major driver of non-stationarity in hydrology in the future (Milly et al. 2008), the reconstructions provide abundant evidence of time periods with statistical characteristics quite different from those of the 20th century.

One example is the 12th century, which was characterized by multiple runs of below-average flow for the Colorado River at Lees Ferry, including a nearly 60-year period (1110–1170) with only 12 years of above-average flow (Meko et al. 2007). The reconstructed flows for the 12th century had lower mean flow, a smaller range of flow values, and a much higher persistence ($r = 0.55$ vs. $r = 0.26$; see Chapter 2) compared to the reconstructed flows for the 20th century. This type of non-stationarity is also seen in wavelet spectra that show changes in the multidecadal variability in reconstructed streamflow over the past six centuries (Woodhouse, Gray, and Meko 2006).

Because of their multi-century to millennial length, reconstructions of streamflow also document variability at time scales longer than what can be discerned from the instrumental record. Time-series analysis reveals a multidecadal peak signal in Colorado River flow at about 50–60 years, suggesting a phasing of wet and dry periods at this interval, although the strength of this phasing varies over time, and it is not clearly associated with a defined climate oscillation such as the AMO or PDO (Woodhouse, Gray, and Meko 2006; Meko, Woodhouse, and Bigio 2017). Such expressions of multi-decadal variability cannot be detected using observed records, given their limited length.

Also due to their extended length, reconstructions contain extremes that may not be represented in the shorter instrumental period, and allow an assessment of events experienced in the observed record in a centuries-long context. Upper Basin reconstructions have documented the unusualness of the high-flow period of the early 20th century as well as droughts more severe than any that occurred in the 20th century. While the ongoing 21st century drought may eventually match the persistence of the longest droughts of the past eight centuries, the medieval period (~850–1300) stands out as an interval of frequent persistent droughts, with multiple runs of eight to ten years of consecutively below average flows. Persistent drought in the 12th century is especially notable, as mentioned above. Statistical analysis suggests that the worst 25-year period of drought in the 12th century—with a mean flow of 84% of the 1906–2004 observed average or less (Meko et al. 2007)—has a probability of occurring once every

six centuries ($p \approx 0.17$, based on 1906–2009 flows) (Meko, Woodhouse, and Morino 2012). On the other extreme, the early 20th century pluvial (1905–1930) has been found to be one of the wettest, if not the wettest multidecadal period in the last 500 years (Woodhouse et al. 2005; Cook, Seager, and Miller 2011) to 1000 years (Cook 2004) across the western U.S., including the upper Colorado River Basin.

The information from the reconstructions of past flow has been useful for providing context for the assessment of observed and GCM-based hydrology (Reclamation 2007c; 2012e). While the record of the past is unlikely to be replicated in the future, the paleohydrology records contain important information about the range of natural variability that has occurred in the past, and thus could occur again. This perspective is especially critical since GCMs do not appear to simulate the full magnitude of decadal to century-scale variability as reflected in long proxy records, including the Colorado River reconstructions (Ault et al. 2013; Woodhouse, Gray, and Meko 2006). The GCMs also appear to underestimate the risk of persistent severe droughts, such as those of the 12th century (Ault et al. 2014). The reconstructions of past streamflow can be particularly valuable in cases where climate models are not very informative or well accepted by practitioners.

Applications in Reclamation-led planning studies

Reclamation first used tree-ring based reconstructions of Colorado River flow in analyses to support the 2007 Interim Guidelines; the analyses based on reconstructed flows were included in Appendix N of the Final EIS (Reclamation 2007b). The reconstructed flow values were used to test the sensitivity of the modeled system in Reclamation's Colorado River Simulation System (CRSS) to a broader range of hydrologic conditions than allowed by the observed hydrology alone. CRSS runs on monthly time steps and requires input for 29 inflow points in the basin (see Chapter 3), while the tree-ring reconstruction that was chosen (Lees 2007), like all such reconstructions, has annual values for a single river location (Lees Ferry). This is a common challenge in using tree-ring reconstructions in water resources planning: system models usually require spatial and temporal inputs at finer resolutions than provided by the annual flow reconstruction. Thus, spatial and temporal disaggregation was a key part of the two methods used by Reclamation to develop CRSS-ingestible hydrologic traces from the (Meko et al. 2007) reconstruction.

The first method, called Direct Paleo or Paleo Resampled, uses the sequences of flow magnitudes directly from Lees 2007. A K-NN approach is used to first disaggregate the annual reconstruction series for Lees Ferry into monthly data by effectively replacing each reconstructed flow value at Lees Ferry (e.g., 1258) with a year and associated monthly values from the observed natural flow record (e.g., 1954) that is sampled from a small set of

“nearest neighbors” to that reconstructed flow value. Then the resulting simulated Lees Ferry monthly flows are disaggregated spatially to all 20 inflow points in the Upper Basin, with the monthly flows at the 9 inflow points in the Lower Basin being taken from the analog year’s observed values (Prairie et al. 2006; 2007). These disaggregated flows (1244 years of monthly flows at 29 sites) are then resampled using the Index Sequential Method (ISM; Chapter 9), generating 1244 unique traces of 53 years in length. Since ISM sequentially block-bootstraps the streamflow data, the generated traces at Lees Ferry consist of the same annual flow magnitudes and sequences as seen in the Lees 2007 reconstruction, with the exception of the 4% of the traces that “wrap” the beginning around to the end of the reconstruction.

The second method, Non-Parametric Paleo Conditioning, reflects the rich variety of flow sequences in the reconstructed flow record (Lees 2007) but constrains the annual values to the range of annual flow magnitudes seen in the observed flow record. The state-transition probabilities—the likelihood that a high-flow year will be followed by a low-flow year, and vice-versa—are extracted from the streamflow reconstruction and then are used to conditionally resample the Lees Ferry observed flows, repeatedly, generating 125 unique traces of 53 years (Reclamation 2007b; 2012e; Prairie et al. 2008; Rajagopalan et al. 2009). The resulting paleo-conditioned Lees Ferry flows are then spatially and temporally disaggregated to monthly inflows at all 29 CRSS inflow points as described above.

Both sets of paleohydrology-informed flow traces, when run through CRSS, showed a higher risk of undesirable system outcomes by the end of the planning period than the flow traces using the observed hydrology (Reclamation 2007b). For example, under the Direct Paleo traces that included the severe and sustained drought in the 1100s, the levels of Lake Powell and Lake Mead declined to levels below their hydropower pools, and in the case of Lake Mead, to dead pool (Figure 10.5). This finding illustrates the value of tree-ring paleohydrology in developing water-supply scenarios that are more stressful than the observed hydrology, and are physically plausible because they are anchored in past hydroclimatic behavior.

In the Basin Study, the same two sets of paleohydrology-informed flow traces were again used as water supply scenarios in CRSS, along with multiple demand and management scenarios, to evaluate system vulnerability and resilience (Reclamation 2012e). A key difference between the Interim Guidelines EIS analyses in 2007 and the Basin Study analyses in 2012 was that the paleohydrologic traces were integral to the main analyses and findings of the Basin Study, rather than being offered as supplementary material in an appendix. Another difference was that, in the Basin Study, the system outcomes under the paleohydrologic traces were compared to

outcomes under traces informed by global climate models (Chapter 11), as well as by the observed hydrology.

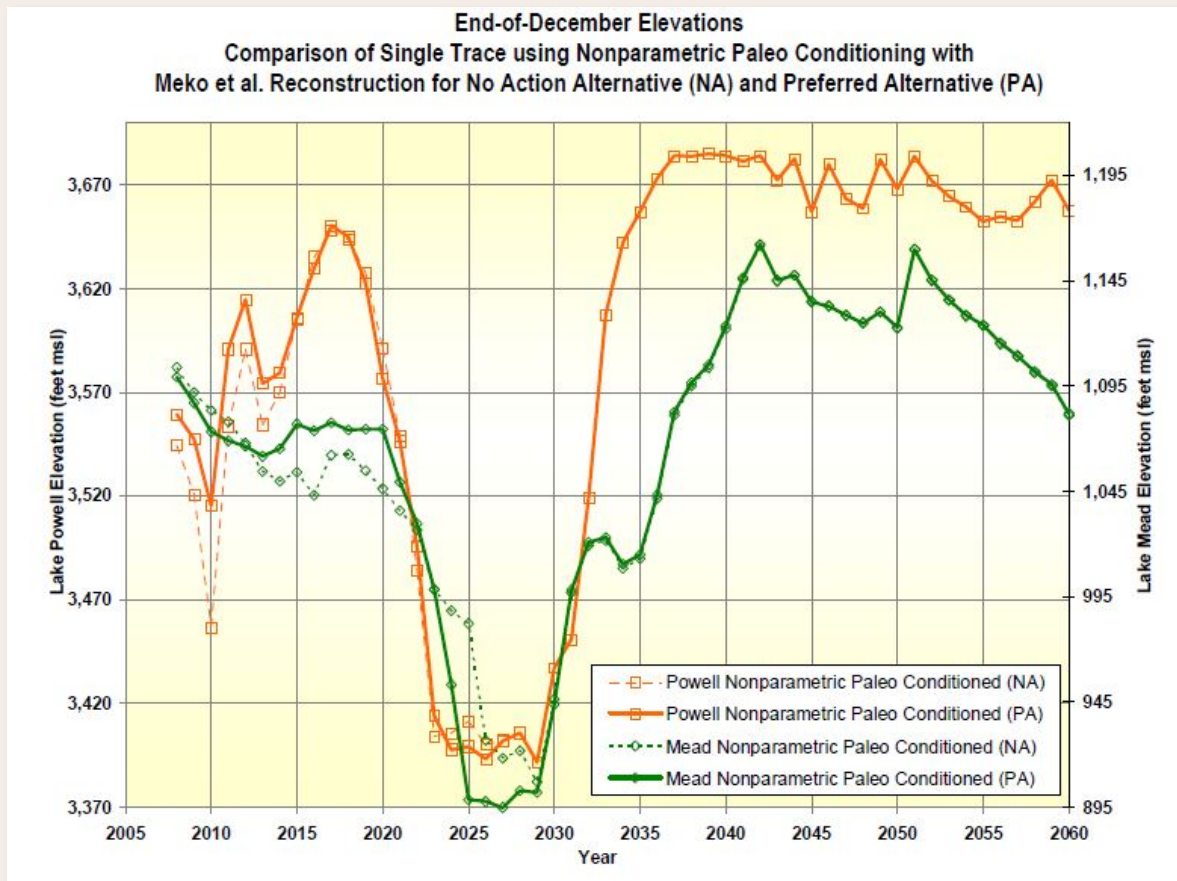


Figure 10.5

Example of the use of paleohydrology-informed flow traces to evaluate Colorado River system vulnerability under plausible hydroclimate futures. Here, Lake Powell elevations for a 53-year period are modeled using synthetic “Paleo Conditioned” flow traces run through the CRSS model under two management scenarios: the No-action Alternative (NA), and the Preferred Alternative (PA), from the 2007 Interim Guidelines Final EIS. The flow traces are based on wet-dry transition information from the Meko et al. (2007) tree-ring reconstruction of Lees Ferry. The drought that occurs in these two scenarios from roughly 2020–2030 does not correspond to a particular reconstructed paleodrought, but is consistent with the statistical characteristics of paleodroughts. (Source: Reclamation 2007b).

Other applications by basin water agencies

Tree-ring reconstructions of streamflow for Lees Ferry and other gages in the basin have been used by several water agencies in diverse applications over the last few decades. These include, most notably, the California Department of Water Resources, Denver Water, and the Salt River Project, who have all funded the development of new tree-ring chronologies,

including new field collections, in addition to new streamflow reconstructions for gages critical to water supplies. Some of these applications, as in the Reclamation analyses, have used reconstructed flows as inputs to water system models to assess system response and sensitivity to extreme events and sequences of flow years that are not represented in the instrumental data records (Rice, Woodhouse, and Lukas 2009). Other agencies have conducted analyses outside of system models to place recent drought events in a long-term context, assess risk of recurrence, and evaluate worst-case scenarios for planning (Woodhouse and Lukas 2006; Meko and Woodhouse 2011; Meko, Woodhouse, and Morino 2012). The reconstructions have also been used to provide a general awareness of the range of hydroclimatic conditions possible, including the frequency and duration of droughts, in communications with boards, elected officials, customers, and the general public (Rice, Woodhouse, and Lukas 2009).

10.5 Tree-ring reconstructions of other hydroclimate variables

Besides annual streamflow, several other hydroclimate variables have been reconstructed for the upper Colorado River Basin. The moisture-limited tree-ring chronologies in and near the basin are largely sensitive to precipitation that falls between the autumn prior to the growing season and the early part of the growing season. The specific window of months to which tree growth is most sensitive varies with species and to some extent, site characteristics (Woodhouse and Pederson 2018). Consequently, it is feasible to reconstruct seasonal moisture variables such as cool-season precipitation and April 1 SWE, for specific regions or sub-basins, as well as for the entire basin (Woodhouse 2003; Gray et al. 2004; MacDonald and Tingstad 2007; Pederson et al. 2011; Woodhouse and Pederson 2018).

The network of existing tree-ring chronologies has also been used for:

- Reconstructing climate and climate-related indices that, like streamflow, reflect an integrative response to hydroclimate, such as annual soil moisture (Anderson, Tootle, and Grissino-Mayer 2012) and the summer Palmer Drought Severity Index (Cook et al. 2004, 2007, 2010)
- Reconstructing a full suite of water-balance variables (e.g., potential evapotranspiration, actual evapotranspiration, SWE, soil moisture storage, and runoff), though with varying degrees of robustness (Gangopadhyay, McCabe, and Woodhouse 2015)
- Developing independent (with respect to chronologies) reconstructions of water-year streamflow and cool-season precipitation to estimate runoff efficiency in the Upper Basin (Woodhouse and Pederson 2018)

Tree-ring reconstructions have also been used to explore the variation in large-scale influences on basin climate and hydrology over past centuries, including El Niño–Southern Oscillation (ENSO; Chapter 2). With several reconstructions of ENSO variability available from tree rings and other proxy data (e.g., Braganza et al. 2009; Gergis et al. 2006), it is tempting to investigate long-term relationships between basin hydroclimate and ENSO. However, as described in Chapter 2, the ENSO influence on Upper Basin streamflow is generally weak. More problematically, there are large differences between the reconstructions of ENSO themselves, adding an additional layer of uncertainty to this type of analysis (Wilson et al. 2010). Similarly, a number of paleo-reconstructions of Pacific Decadal Oscillation (PDO) have been generated (Biondi, Gershunov, and Cayan 2001; D’Arrigo, Villalba, and Wiles 2001; Gedalof, Mantua, and Peterson 2002; MacDonald and Case 2005). While these reconstructions show a great deal of consistency during the post-1900 calibration period, they greatly diverge prior to the 20th century, suggesting that the PDO itself may be unstable over space and time (Wise 2015), or that the teleconnected influences on western North America climate are unstable.

10.6 Blending paleohydrology and climate change information

The record of past hydroclimatic variability will not be exactly replicated in the future because of the large random component of natural variability, as well as the unprecedented impacts of human activities on climate. While the modes and expressions of natural variability as documented in the reconstructions may be significantly altered by future human-caused climate forcing, there has been very little research to examine such potential changes. Thus, in the absence of evidence to the contrary, it is safer to assume that these modes and expressions of variability will continue. As far as we know, there is no reason that an event such as the severe and sustained drought of the mid-1100s could not occur in the future.

As noted above, the main value of the tree-ring reconstructions is in their broader and richer sequences of wet and dry years, compared to the instrumental record. This information can be combined with the most robust aspects of climate projections from GCMs (i.e., future warming) to develop plausible scenarios for future hydrology. There have been several past and ongoing efforts to blend paleohydrology and climate-change information.

Brekke et al. (2009) explored ways to represent information in both climate projections and paleoclimate data (in this case, runoff statistics) to inform water supply planning assumptions, using the Gunnison River as one of two

test cases. Gray and McCabe (2010) demonstrated an approach that used a water-balance model to blend long-term precipitation variability with warming temperatures to produce projections of streamflow and drought for the upper Yellowstone River in Montana. In the Colorado River Water Availability Study (CWCB 2012), projected temperature changes and precipitation changes from GCMs were used in a hydrologic model (VIC; Chapter 6) to alter historical flow values, which were then re-sequenced into synthetic flow traces using information from the Meko et al. (2007) Lees Ferry reconstruction and Reclamation's "paleo-conditioning" method as described earlier. An ongoing project funded by the DOI Southwest Climate Adaptation Science Center includes the development of an approach that blends tree-ring reconstructed basin cool-season precipitation with warmer temperatures consistent with GCM projections. The approach uses synthetic temperature series elevated by 2° to 4°C, or incorporating a warming trend, to generate streamflow using the McCabe and Wolock (2011) water-balance model.

10.7 Challenges and opportunities

Tree-ring paleohydrology is a relatively mature science, with a 75-year history, and the recent reconstructions of Colorado River (Lees Ferry) streamflow collectively provide a very robust view of pre-1900 hydrologic variability from interannual to century time scales. There are unlikely to be significant future improvements in the already high skill of these reconstructions. But there is more work to be done to refine the application of the reconstructions in water-supply planning, including establishing a stronger conceptual and practical basis for merging the reconstructions with future projections of streamflow.

Challenge: Updating chronologies and reconstructions

At present, only seven tree-ring site chronologies in the Upper Basin extend beyond 2005, so current streamflow reconstructions do not have the benefit of full calibration against the early 21st century dry period. Additionally, Reclamation's ongoing revisions of natural flow estimates (Chapter 5) may, cumulatively, substantially revise the target hydrology for tree-ring flow reconstructions.

Opportunities

- Develop new or updated tree-ring site chronologies that can be included in the calibration of any forthcoming streamflow reconstructions.
- Consider recalibration of, as well as assessment of the sensitivity of, the tree-ring flow reconstructions to the revised natural flows.

- Generate new, targeted reconstructions for the key water supply regions of the Upper Basin like the ongoing project funded by the USGS Southwest Climate Adaptation Science Center, in collaboration with basin water managers.

Challenge: Blending paleo with climate projections

Key to applications of paleohydrology to future climate scenarios is understanding how modes of natural variability itself will change over the coming decades. It is unclear which methods of blending paleohydrology data and climate projections have the most robust physical foundation, and more work is needed to examine the issue of persistence in streamflow reconstructions and to determine its source.

Opportunity

- Develop plausible scenarios and characteristics of future basin drought over the next several decades through integration of paleohydrology data and climate projections. Some of this work is underway, as described above.

Challenge: Reconstructions of temperature

Existing tree-ring reconstructions of annual and growing-season temperature for the basin are not nearly as skillful as reconstructions of precipitation and streamflow, limiting our ability to tease apart the drivers of past low-flow periods and place the recent warming trend in context.

Opportunity

- Renew efforts to develop a robust reconstruction of past basin temperatures, building on current investigations using bristlecone pine, plus updating and re-measuring other collections of trees that are limited in growth by temperature.



Chapter 11

Climate Change-Informed Hydrology

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Key points

- Climate change-informed hydrology is increasingly used in basin planning studies to complement other long-range hydrologic information.
- Most approaches to developing this information begin with global climate models (GCMs) driven by one of several emissions scenarios; the approaches incorporate multiple processing steps, with corresponding methodological choices that each have implications for the final output and its uncertainty.
- GCMs are the best tools we have for exploring and quantifying physically plausible future climate changes at global to sub-continental scales. They have deficiencies in representing some key climate system features relevant to basin-scale climate, as well as reproducing historical basin-scale climate patterns themselves.
- Downscaling methods make GCM output more usable for finer-scale hydrologic modeling, such as projections of future streamflows. Downscaled projections are not necessarily more accurate than the underlying GCM output in depicting future climate change.
- Further warming is projected by all GCMs to continue in the basin as a consequence of continuing greenhouse gas emissions; basin temperatures are projected to rise by 2.5°F–6.5°F by mid-century relative to the late 20th century average.
- The direction of future precipitation change for the basin is much less certain than temperature change. The GCMs show some overall tendency toward increasing annual precipitation in the northern parts of the Upper Basin, and toward decreasing precipitation from the San Juan Basin south through the Lower Basin.
- The projected trends in precipitation are relatively small compared to the high year-to-year natural, or internal, variability in precipitation. Most GCMs project increased precipitation variability in the future.
- Mainly due to the pervasive effects of warming temperatures on the water cycle, nearly all of the many datasets of climate change-informed hydrology and related studies show a strong tendency toward lower annual runoff volumes in the Upper Basin and the Lower Basin, as well as reduced spring snowpack and earlier runoff.
- The overall spread of potential future hydroclimatic changes for the basin, as depicted across the GCM-driven projections, has not been reduced over the past decade and may not be appreciably reduced by forthcoming data and methods, not least because much of the spread is due to unpredictable natural climate variability.

11.1 Overview

The last decade has seen basin water planning activities increasingly informed by expected future climate change and its effects on hydrology. The development and use of climate change-informed hydrology was largely confined to the research community prior to 2010, with few applications in real-world water planning activities in the western U.S. Appendix U of the Final EIS for the Interim Guidelines (Reclamation 2007c) set a pathway for consideration of climate change projections and their incorporation in water planning for the basin. Since then, there has been a broad shift toward greater use of these data by water agencies at the federal, state, and local level in the Colorado River Basin and elsewhere in the West, although with substantial variation in the pace and extent of adoption by different agencies and stakeholders. There has also been rapid growth in methodologies and available datasets, with agencies such as Reclamation and U.S. Army Corps of Engineers (USACE) becoming directly involved with data development, and leading interagency efforts to advance both the science and practice in this area (Brekke et al. 2009; Brekke 2011; Raff et al. 2013). The Water Utility Climate Alliance (WUCA), a self-organized consortium of major municipal water utilities, and its partners have also been instrumental in facilitating the development of climate change guidance for water managers (e.g., Barsugli et al. 2009; Vogel 2015).

Climate change-informed hydrologic traces have been used as an adjunct to traces based on observed hydrology and paleohydrology in basin-scale planning studies, and also on their own to drive climate change impact assessments (see the Volume IV introduction). Virtually all approaches to developing climate change-informed hydrology, whether in the Colorado River Basin or elsewhere, begin with the output of GCMs—an acronym that originally referred to “general circulation models” but has come to also represent the more inclusive category “global climate models.” The GCMs translate the expected climate “forcings” (greenhouse gases, aerosols, and land use changes) on the Earth’s energy balance into future climate changes at global and regional scales, but they run at too coarse a resolution (typically 100 km or greater) to directly produce robust basin-scale hydrology outputs that are usable for water planning in the basin. Several different methods, involving varying intermediate steps and methodological choices, may be used to derive basin-scale climate change-informed hydrology from GCM output (Figure 11.1).

In the method that has been most often used, including in recent basin planning studies (e.g., Reclamation 2012e, 2018), emissions scenarios are used to drive GCMs, and the climate output of the GCMs is bias-corrected and downscaled, then run through a separate (off-line) hydrologic model (Figure 11.1; the pink arrows show this pathway). At each step, described in Table 11.1, there are subjective decisions that a modeler or data analyst must

make, which partially indicates the uncertainties associated with that model or data type. The uncertainties collectively carry forward into the final result (simulated future hydrology), although not necessarily in a straightforward, additive manner.

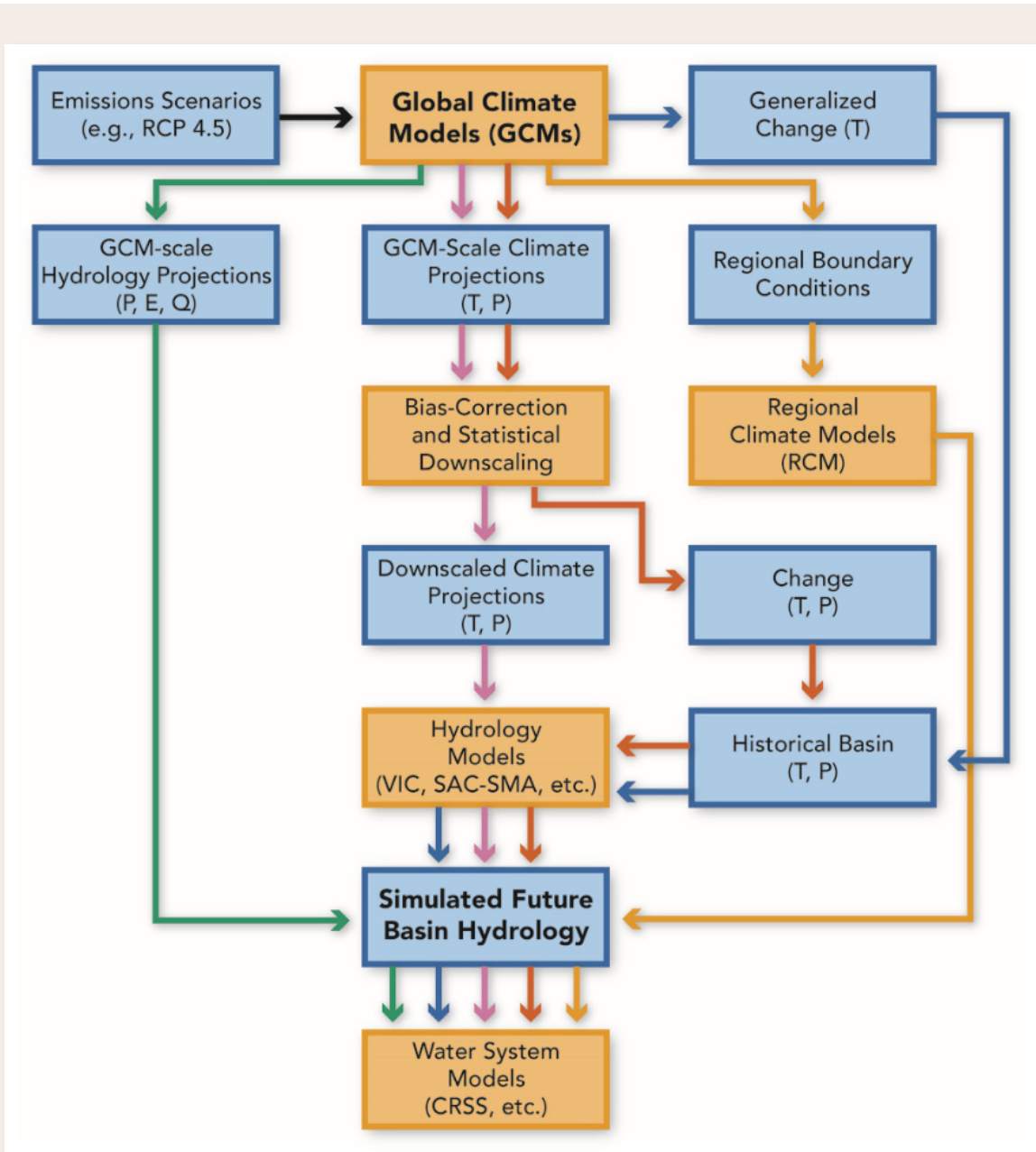


Figure 11.1

Schematic showing five different approaches (colored arrows) for developing climate change-informed hydrology from global climate model (GCM) output that have been tested or implemented for the Colorado River Basin. The pathway shown with the pink arrows has been the most frequently used in recent basin planning studies. Blue boxes show data inputs/outputs, while orange boxes show modeling steps. See also similar schematics in Ray et al. (2008) and Vano et al. (2014).

Table 11.1

Key steps in the typical pathway for producing climate change-informed projections of future hydrology, objective of that step, and challenges related to that step.

Step in modeling chain	Objective of this step	Caveats
Emissions scenarios	Provide multiple trajectories of future levels of global climate forcing (mainly from greenhouse gases) so that GCMs can project the future climate changes associated with an integrated storyline of future population growth, energy use, and policy.	Scenarios often have been lumped together in hydrologic impact studies, but this should be avoided. Probabilities have not been assigned to the scenarios.
Global Climate Models (GCMs)	Provide estimates of future changes in atmospheric circulation and in key climate variables, at global to continental scales.	The simulated natural (internal) variability in GCM projections means that large ensembles of simulations are required to robustly estimate mean changes.
Bias-correction	Shifts the values of GCM-simulated climate variables to better match historical observations of those variables (both mean and variability).	Some GCM biases cannot be meaningfully corrected. Bias-corrected data can mislead users about the ability of the underlying GCMs to simulate historical climate.
Downscaling	Translates coarse-scale GCM climate output statistically or dynamically into finer-scale climate output suitable for regional climate analysis and impacts modeling.	Most downscaling methods implicitly assume that spatial relationships or other characteristics of observed climate are maintained in the future (i.e., stationarity). Can mislead users about the reliability of the spatial and temporal details of the regional output.
Hydrologic modeling	Translates finer-scale climate output into future trajectories of hydrologic variables (e.g., runoff) at basin and watershed scale.	Hydrology models are calibrated to historical climate and may have stationarity assumptions embedded in their parameters.

Methods that develop basin-scale hydrologic simulations from GCMs in order to drive a water system model are aligned with “top-down” approaches to climate change impact assessment, where one starts with global-scale climate projections, ultimately arriving at local changes and impacts that are determined by those top-level inputs in combination with the intervening data and models. In comparison, “bottom-up” approaches typically begin with local system vulnerabilities to determine thresholds of undesirable impacts, then query higher-level climate information to assess the future changes in exceedances of system thresholds. In practice, climate impact or vulnerability assessments often end up as hybrids of top-down and bottom-up approaches. When one begins an assessment process with a large set (ensemble) of global climate projections, as is typically done, there is usually an equally large ensemble of local or basin-scale simulations at the end, with each of those simulations retaining important characteristics of the respective climate projection that drove it. The handling and interpretation of these simulations strongly influence how the data ultimately inform planning decisions.

The organization and content of this chapter acknowledges that the top-down, large-ensemble approach is strongly embedded in current practice, including recent and forthcoming hydrologic analyses and planning studies for the basin (e.g., Reclamation 2012e; 2018; 2020). Thus, this chapter follows the typical processing steps from GCMs to basin-scale hydrology, providing information on models and methods as used to generate ensembles of climate change-informed hydrology, and summaries and evaluations of the output of those ensembles. However, there are alternative approaches to using climate change information to understand potential future hydrology—those alternatives will be described toward the end of this chapter.

Those readers with greater familiarity with the processing steps and models (GCMs, emissions scenarios, downscaling) and who are most interested in the results—projected future climate and hydrology for the Colorado River Basin—are encouraged to jump ahead to sections 11.6 and 11.7.

11.2 Understanding GCMs and climate projections

As noted above, GCMs are the usual starting point for methods for producing climate change-informed hydrology, such as can be run in a water system model like CRSS. GCMs are designed to simulate the dynamics of the atmosphere, oceans, land surface and vegetation, sea ice, land ice, and the energy balance and water balance that integrate these components of the climate system. Overall, they provide realistic simulations of the key physical phenomena such as the planetary energy

balance, large-scale atmospheric and oceanic circulation, broad-scale patterns of temperature and precipitation, and statistical characteristics of the historical and current climate, at global scales. At the scale of regions the size of the Upper Basin, the simulations are not as realistic, especially for precipitation, as detailed below.

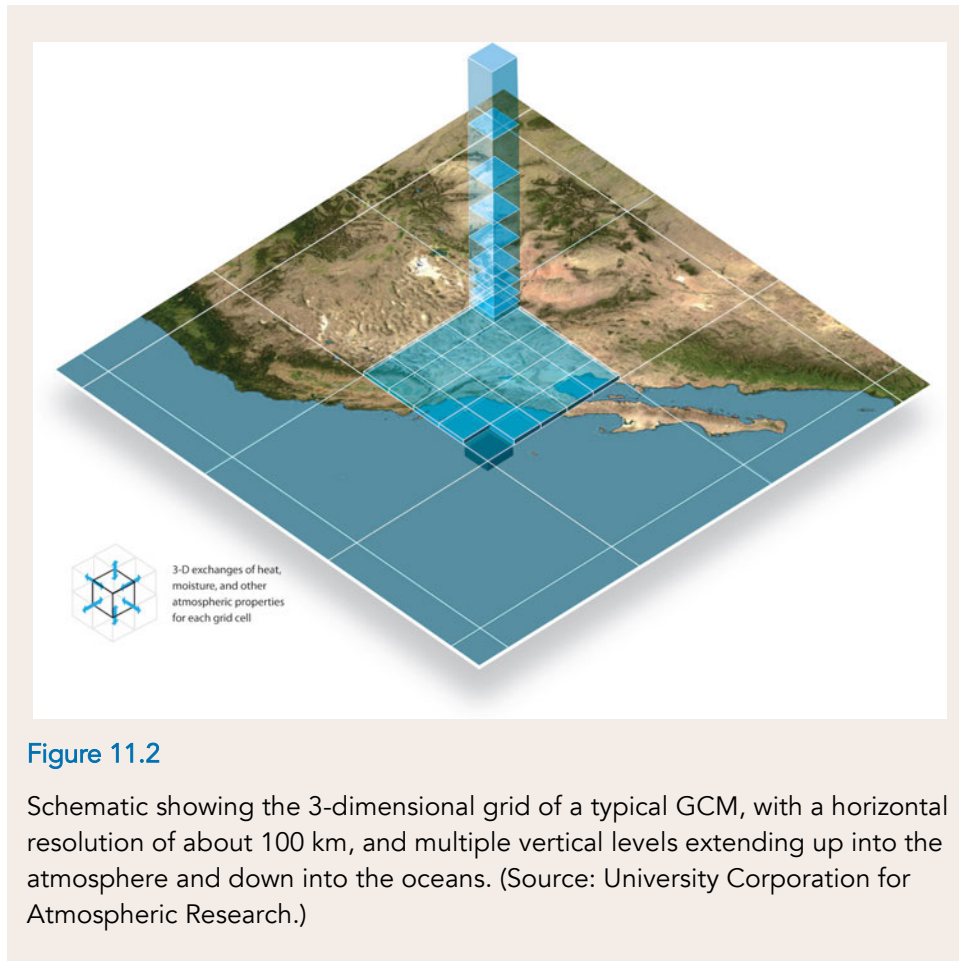


Figure 11.2

Schematic showing the 3-dimensional grid of a typical GCM, with a horizontal resolution of about 100 km, and multiple vertical levels extending up into the atmosphere and down into the oceans. (Source: University Corporation for Atmospheric Research.)

The typical structure of a GCM divides the globe—the atmosphere and oceans—into a grid in both the horizontal and vertical dimensions, creating grid boxes (Figure 11.2). In GCMs, as in weather and climate forecast models (Chapter 7), fundamental physical laws of thermodynamics, motion, and fluid dynamics are used to simulate many of the processes, such as the transfer of mass, energy, and momentum between the grid boxes. Other processes, such as the formation of clouds and thunderstorms, take place at spatial scales smaller than a model grid box (typically 100-250 km across). Climate models simulate these sub-grid-scale processes by using numerical factors (parameters) that have been generalized from observations to the grid box scale, a procedure called parameterization. Higher resolution (i.e., smaller grid boxes) allows for more physically explicit representation of processes, as well as more realistic depiction of topography, both of which tend to improve model performance. But higher

resolution comes with much greater computational costs; increasing model resolution both horizontally and vertically by a factor of two requires eight times as many calculations.

From a handful of models at a few modeling centers in the 1980s, the GCM community has grown to over 30 modeling centers in 10 countries. These centers have developed and now maintain at least 60 GCMs. It is important to emphasize that these have not been wholly independent efforts; the modeling centers share model code and parameters for many processes, and several centers maintain multiple GCMs that are variants of each other.

Climate projections

For a given climate simulation, a GCM is initialized with a long period to “spin up” the ocean and other slowly evolving model components from specific starting observations of the atmosphere and oceans, and then the GCM is allowed to run freely in time to simulate the past climate or to make long-term projections of future climate. Climate models are marched forward from the initial state at time steps ranging from a few minutes to an hour. This high temporal resolution means that GCMs actually simulate sequences of hourly and daily weather, which integrate over time into modeled climate variability and change at longer timescales. After the initial state is specified, the only inputs to the GCM are so-called “external forcings,” such as solar variations, aerosols from historical volcanic eruptions, and the changes in greenhouse gas concentrations, ozone, and anthropogenic aerosols collectively specified in an emissions scenario. Recently, historical observations and future scenarios of land cover change, which can exert regional influences on climate, have been included in many models.

A simulation of future climate from a GCM is called a projection, rather than a prediction or forecast, because it is conditional on a particular set of assumptions about future greenhouse gases and other climate forcings. The assumptions reflect an integrated storyline of future population growth, energy use, and policy (emissions scenarios; section 11.4). For any given climate variable, the GCM projection will show a combination of 1) simulated natural (“internal” or “unforced”) variability and 2) a forced change over time, if that variable is affected by changes in external forcing (most prominently, rising greenhouse gases).

A critical difference among GCMs is how each one simulates the feedback mechanisms that are expected to amplify the direct forcing of the climate from greenhouse gases, mainly involving clouds and water vapor. The strength of these feedback mechanisms is uncertain, and thus the models show a range of global temperature responses to given increments of greenhouse gases, which then translates into similarly broad ranges for projected temperatures at regional scales.

GCM performance and credibility

Unlike short-term forecasts from weather models, which can be readily validated by frequent comparison with observations of the actual weather over the forecast period, the multidecadal future projections from climate models cannot be validated directly. Thus, the main way that the credibility of GCMs is established is by comparing their simulations of the historical period, over different spatial scales, with the observed climate over that period. Such comparisons examine both the models' reproduction of the statistics of climate—averages, ranges, and extremes—and the models' fidelity to the dynamical features of key climate processes. These comparisons can also be used to evaluate the relative performance of the GCMs, with the important caveat that performance over the historical period may not be reflective of a model's skill in accurately predicting the future changes in climate.

Assessing the ability of GCMs to reproduce the dynamical features and statistics of the historical climate, one can make the generalizations listed below (Barsugli et al. 2009; Lukas et al. 2014; USGCRP 2017; Reclamation 2020).

Performance at global to continental scales (1,000 km to 10,000 km)

What GCMs reproduce well in their raw output:

- Temperature: Spatial and seasonal patterns (i.e., monthly and annual averages), and recent warming trends
- Precipitation: Spatial and seasonal patterns (i.e., monthly and annual averages), but not as well as for temperature
- The dominant seasonal patterns of high and low pressure
- The jet stream and its seasonal north-south movement

What GCMs do not reproduce as well in their raw output:

- Precipitation: Daily amounts—too little variability (“GCM drizzle”)
- ENSO: the pattern and cycle is present in nearly all models, but the spatial features are unrealistic in some important respects

Performance at the scale of the Colorado River Basin (<1,000 km)

What GCMs reproduce well in their raw output:

- Temperature: Seasonal cycle and recent warming trends

What GCMs do not reproduce as well in their raw output:

- Temperature: Spatial patterns—these are largely driven by topography which is smoothed out in GCMs
- Temperature: Regional annual average—can differ from observed by +/- 6°F
- Temperature: At mountain-top level—too warm because GCM-modeled mountains are too low

- Precipitation: Annual amounts—nearly all GCMs overestimate by 50-150%
- Precipitation: Seasonal cycle (monthly averages)—few GCMs replicate the observed pattern
- Precipitation: Spatial patterns—these are largely driven by topography which is smoothed out in GCMs
- Precipitation: Daily amounts—insufficient variability; heavy and extreme events are too small/infrequent
- ENSO signal in the region’s precipitation—generally weaker than actual

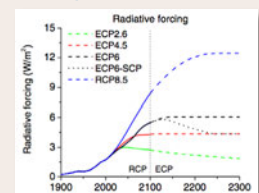
Many of the deficiencies listed above stem from the relatively coarse spatial resolution (>100 km) of most GCMs and their inadequate representation of the complex topography of the western U.S. These deficiencies can be addressed to varying degrees using regional downscaling methods (section 11.5), which also include a bias-correction step that corrects for the systematic errors in GCM-simulated temperature and precipitation described above.

11.3 The CMIPs: Standardized collections of GCM projections

In the 1990s, the global community of climate modelers recognized the need for standardized sets of climate model runs, with consistent inputs, time periods to simulate, and historical and future greenhouse gas scenarios; i.e., emissions scenarios (section 11.4). This would facilitate systematic evaluation of model outputs to improve understanding of climate dynamics and to improve the models themselves. These efforts evolved into the World Climate Research Programme’s (WCRP’s) Coupled Model Intercomparison Project (CMIP). The third phase, called CMIP3, was carried out to support the IPCC’s Fourth Assessment Report (AR4), while the most recent phase, CMIP5 (there was no CMIP4), supports the IPCC Fifth Assessment Report (AR5). The next phase, CMIP6, is in progress and will support the IPCC Sixth Assessment Report, which is expected in 2021. A list of the modeling centers and the GCMs for which CMIP5 projections are available can be found on this NOAA [webpage](#).

Each CMIP can be thought of as an organized roundup of the output of the latest (at the time) generation of GCMs. Nearly all GCM output used in regional and national climate assessments and in basin-scale water resource planning studies since 2008 have come from CMIP3 or CMIP5 or both. Compared to CMIP3, CMIP5 included more participating modeling centers and GCMs, generally higher-resolution models, more complete physical parameterizations of key climate processes and more individual

Models Represented in NOAA's Climate Change Web Portal



Link:
<https://esrl.noaa.gov/pd/ipcc/cmip5/help.html>

projections of future climate. It appears that CMIP6 will see the continuation of all of these trends. The differences between CMIP3, CMIP5, and CMIP6 are summarized in Table 11.2.

Table 11.2

Key characteristics of the Coupled Model Intercomparison Project (CMIP) and participating GCMs in Phase 3 (CMIP3), Phase 5 (CMIP5), and the forthcoming Phase 6 (CMIP6) and applications of GCM data from CMIP3 and CMIP5. (Source: updated from Lukas et al. 2014; CMIP6 information from Hausfather 2019)

	CMIP3	CMIP5	CMIP6
Initial data availability	2006	2012	2019-2020
Main Emissions Scenarios (count) See section 11.4 for explanation and acronyms	(3) SRES: B1, A1B, A2	(4) RCP: 2.6, 4.5, 6.0, 8.5	(9) SSP-RCP: SSP1-1.9, SSP1-2.6, SSP2-4.5, SSP3-7.0, SSP3-LowNTCF [6.3], SSP4-3.4, SSP4-6.0, SSP5-3.4-OS, SSP5-8.5
Historical climate period	1880–2000	1850–2005	1850-2014
Projection period	2001–2100	2006–2100+	2015-2100+
Number of modeling centers	16	30	49
Number of models	22	55	100
Number of model simulations (projections) for core future scenario runs	120	250	>300?
Range of horizontal resolutions (average grid cell size)	100-500 km (median: 250 km)	60–250 km (median: 150 km)	25–250 km
Timestep of archived data	Monthly	Daily and monthly; some sub-daily	Daily and monthly; some sub-daily
Decadal Prediction?	No	Yes, 2010–2035	Yes
Selected climate assessments using these projections	IPCC AR4 (2007) <i>Climate Assessment of the Southwest</i> (2013) <i>Climate Change in Colorado</i> (2008)	IPCC AR5 (2013) <i>National Climate Assessment</i> (NCA3, 2014; NCA4, 2018) <i>Climate Change in Colorado</i> (2014)	IPCC AR6 (2021)
Selected Colorado River Basin hydrology studies using these projections	<i>Colorado River Water Availability Study–Phase 1</i> (2012) <i>Colorado River Basin Supply and Demand Study</i> (2012)	<i>Colorado River Water Availability Study–Phase 2</i> (2014) <i>Draft CMIP5 Report</i> (Reclamation 2020)	

Participation in CMIP is open to all modeling centers, limited only by their ability to use the standardized inputs for a given CMIP “experiment” and produce runs in the specified output format. There are no formal criteria for model quality, reliability, or skill. However, any model that was unusually poor at reproducing the historical climate, or produced future projections whose results were well outside the bounds of the other models, would be unlikely to be put forward for participation in CMIP by the modeling center that developed it (Knutti 2010; Knutti, Masson, and Gettelman 2013; Sanderson, Wehner, and Knutti 2017; Eyring et al. 2019).

As noted earlier, climate models are not independent of each other: they share assumptions, simulation methods, and even code and parameter sets, and during development they are compared to the same set of historical observations. Collaboration among modeling centers also means that models that have high skill tend to be the ones that perform similarly to other models (Sanderson, Wehner, and Knutti 2017). Consequently, the effective number of models (i.e., sample size) in the CMIP ensembles is smaller than the nominal number of models (Tebaldi and Knutti 2007; Knutti, Masson, and Gettelman 2013; Sanderson, Wehner, and Knutti 2017). Because the resulting ensembles of model projections are neither a random nor systematic sample of potential future climate, the distribution of future projected changes should not be treated probabilistically. This issue is explored at greater length in the last section of this chapter.

Is CMIP5 better than CMIP3? Will CMIP6 be better than CMIP5?

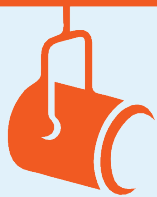
While GCMs have continued to improve from one generation to the next, in the recent update cycles this progress has been more incremental than fundamental. The projections archived in CMIP5 are generally better than those in CMIP3, according to various performance metrics, but not so much better as to invalidate the results of analyses done with CMIP3 (Knutti et al. 2010; Lukas et al. 2014; Reclamation 2020). The CMIP3 and CMIP5 model ensembles show very similar average projections for temperature and precipitation changes over much of the globe, including most of North America, and a similar range of uncertainty across the models. For the Colorado River Basin, there was very little difference in the temperature projections between the CMIP3 and CMIP5 ensembles, after accounting for the differences in the emissions scenarios, but for precipitation, the CMIP5 projections were slightly shifted toward wetter outcomes than CMIP3, and this difference is accentuated by certain downscaling methods, as described later.

Similarly, the forthcoming CMIP6 models and their projections will be improved from CMIP5 in some technical respects (e.g., model resolution), and will probably have overall better performance in reproducing features of the observed climate. But judging from the previous CMIPs, CMIP6 should be expected to show similar spatial patterns of future change as

CMIP5 and CMIP3, and similarly broad ranges of future change, as CMIP5 and CMIP3. In other words, the overall CMIP6 ensemble seems unlikely to reduce uncertainties related to model structure (Table 1.4).

Enough of the CMIP6 model results have been released for analysts to discern that the CMIP6 models are showing, on average, warmer future global temperatures than CMIP5 given equivalent emissions scenarios (Hausfather 2019). This indicates that, compared to their CMIP5 counterparts, many of the CMIP6 models are simulating even stronger positive feedbacks (e.g., from clouds, water vapor, and surface reflectivity) that enhance the direct warming from the additional greenhouse gases. However, Tokarska et al. (2020) found that the CMIP6 models with higher future warming also tend to overestimate the observed global warming trend from 1981–2017; adjusting the CMIP6 projections to account for this tendency brings the overall CMIP6–projected warming into line with that depicted by CMIP5. It is too soon to know whether the adjustment to the CMIP6 ensemble proposed by Tokarska et al. (2020) will be more broadly accepted, e.g., to be implemented in downscaled CMIP6 datasets developed for application purposes.

In addition to the main set of 21st century climate projections from CMIP6 intended for use in climate change assessment (“ScenarioMIP”; O’Neill et al. 2016), there will be a separate set of projections run using high-resolution climate models (“HighResMIP”; Haarsma et al. 2016). At least 20 GCMs that run at 50-km horizontal resolution or better are participating in HighResMIP; this resolution is comparable to the regional climate models in NARCCAP and NA-CORDEX (see section 11.5). HighResMIP may be able to provide additional insights into potential changes in atmospheric and ocean dynamics influencing the western U.S.



Screening and weighting the GCM ensemble

The large size of the CMIP3 and CMIP5 ensembles (20–35+ GCMs, 100–200+ projections) and the broad range of projected future changes across the ensembles, make it challenging to analyze and interpret future climate projections. It would seem logical to try to reduce the size or otherwise refine the CMIP ensembles by evaluating the performance of the GCMs and then culling models that perform poorly or weighting the model projections according to their performance. For the most recent National Climate Assessment (USGCRP 2017), the GCM projections were weighted, but not screened to reduce the ensemble.

Over the past decade, researchers have tested different approaches for evaluation, screening, and weighting for projections of future climate for the western U.S. (Brekke et al. 2008; Pierce et al. 2009; Mote et al. 2011; Reclamation 2020; Rupp et al. 2013; Rupp, Abatzoglou, and Mote 2017). Nearly all of these efforts have found that weighting or screening the GCM ensemble has little or no effect on the distribution of future climate changes, assuming at least 10 of the models (i.e., 30–50% of the original ensemble) are retained. Also, looking across those efforts, one can see that performance rankings of models can vary with different performance metrics. In all cases, as mentioned earlier, those metrics are based on the model's ability to reproduce average statistics and spatial patterns of the observed climate, with the implicit but untestable assumption that models that better simulate the observed climate will perform better in predicting future climate changes.

For performance-based screening and weighting to have a significant and meaningful effect on the ensemble, there must be a clear relationship between model performance and the sign/magnitude of the model's projected future change. This condition, however, is rarely met in evaluations of GCM performance, including the case discussed in more detail below. One exception was from Rupp, Abatzoglou, and Mote (2017), who found that the GCMs that better reproduce the historical climate of the Columbia River Basin tend to project greater warming and larger precipitation increases than the other GCMs, though these results depended on the method of evaluating the GCMs.

If a screening procedure does reduce the original ensemble to fewer than 10 models (i.e., eliminating more than 70% of the 30+ CMIP5 models) any theoretical beneficial effect of screening out low-performing GCMs may be outweighed by the risk of under-sampling model uncertainty. In other words, the screened ensemble distribution may become too narrow, and exclude outlying but still plausible climate outcomes that one would want to consider in risk assessment and planning (Mote et al. 2011).

Comprehensive and basin-specific screening and weighting procedures were performed for the forthcoming report, “Exploring Climate and Hydrology Projections from the CMIP5 Archive” (Reclamation 2020). A set of 52 CMIP3 and CMIP5 GCMs were first screened against global performance metrics (Gleckler, Taylor, and Doutriaux 2008; Flato et al. 2013), removing 13 of the models. The remaining 39 models (12 from CMIP3, 27 from CMIP5) were then assessed against a set of 48 region-specific metrics that address the ability of the GCM to reproduce 1) the basic statistics of Colorado River Basin temperature and precipitation; 2) the amplitude and phase of seasonal cycles of temperature and precipitation; and 3) ENSO and PDO mean Sea Surface Temperature (SST) pattern and signal spectrum, and the teleconnected temperature and precipitation response over the western United States. The output of the retained 39 GCMs was then weighted according to overall performance on the set of region-specific metrics, with the best-performing GCM being given roughly 2.5 times the weight of the worst-performing GCM.

The projections of hydrologic changes shown by the different ensembles—“Full” (all GCMs), “Retained” (after screening against the global metrics), and “Retained and Weighted” (after evaluation against the regional metrics)—are shown in Figure 11.3. There are only slight differences in the distribution of streamflow changes after the initial screening, and even smaller differences imparted by the weighting procedure (column on far right).

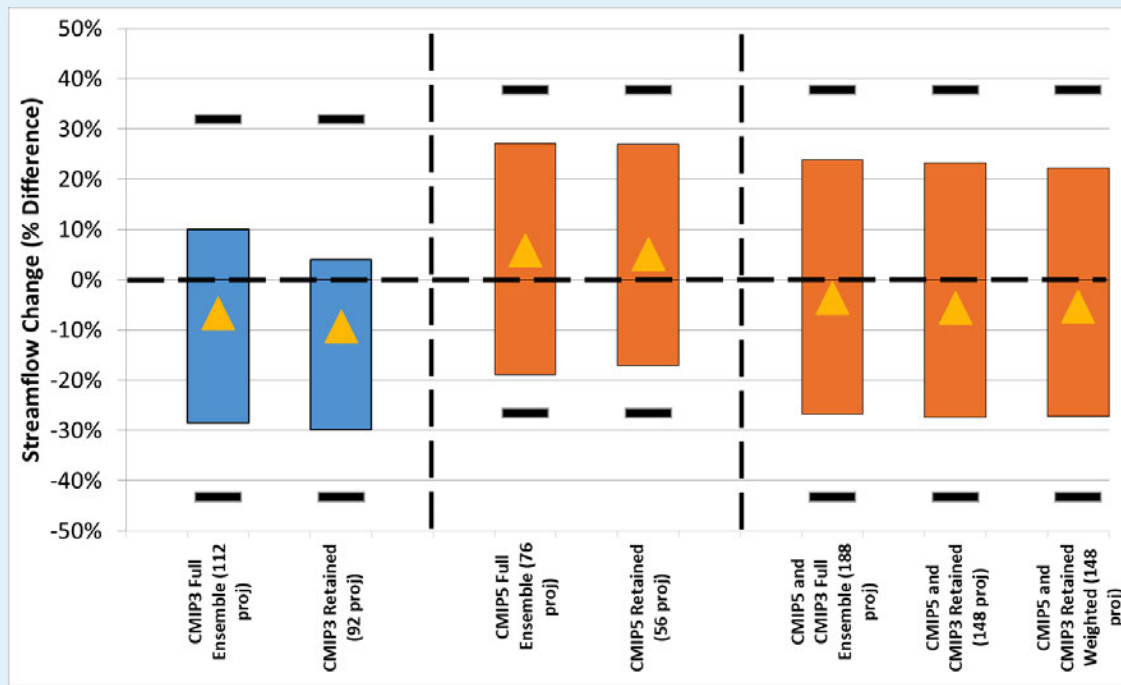


Figure 11.3

Projected changes in VIC-modeled streamflows at Colorado River at Lees Ferry for the end-of-century period (2066–2095) relative to the historical period (1971–2000), from the Full, Retained, and Retained and Weighted CMIP3 and CMIP5 GCM ensembles. Triangles are ensemble means, bars show the 10th and 90th percentiles range, and horizontal lines are minimum and maximum projections. (Source: Reclamation 2020)

Given the apparent lack of impact on the distribution of projected changes in climate and hydrology, the main value to screening and weighting procedures may be in imparting greater credibility to the results. Since screening and weighting of CMIP3 and CMIP5 GCMs specific to the Colorado River Basin has already been performed (Reclamation 2020), it makes sense for those refined ensembles to be used in future analyses for the basin. Potentially, the same analyses could be performed for the CMIP6 models when those data become available, though the value of doing so would likely be more in identifying performance differences between CMIP6 and CMIP5, than in refining the CMIP6 ensemble itself.

11.4 Emissions scenarios used to drive GCMs

Since anthropogenic greenhouse gas emissions have been identified as the primary cause of recent global warming and other climate changes (USGCRP 2017), it is necessary for future climate simulations from GCMs to have inputs that describe how greenhouse gas emissions and concentrations will unfold over the next century and longer. A single “best” forecast of future emissions would be fraught with very large uncertainties, so the modeling community has adopted a set of multiple standardized trajectories whose range is intended to capture those uncertainties.

The CMIP5 standardized greenhouse gas trajectories are called Representative Concentration Pathways (RCPs), which replaced the SRES (Special Report on Emissions Scenarios) emissions scenarios (e.g., B1, A1B, A2) that were used in the GCM projections for CMIP3. Both the RCPs and the SRES scenarios provide plausible trajectories of GHG emissions and concentrations that are each linked to future trends in demographic, socioeconomic, technological, and political factors. Since those underlying trends cannot be predicted with any confidence, there have been no probabilities assigned to any one of these RCPs being the actual future path.

Each CMIP5 GCM simulation or projection uses one of the four RCPs: RCP 2.6, RCP 4.5, RCP 6.0, or RCP 8.5 (Figure 11.4). The numbers refer to the strength of the global radiative forcing by year 2100, in watts per square meter (W/m^2)—the extra energy trapped in the climate system by added greenhouse gases and other human-caused changes—compared to pre-industrial levels. As with the SRES scenarios, the divergence among the RCPs at mid-century is much smaller than later in the century. The projected increase in global average temperature by 2100 for any given GCM closely corresponds to the radiative forcing of each RCP.

- RCP 2.6 (low) assumes immediate and very large (about 70%) reductions in GHG emissions from today’s levels, and its climate forcing peaks by 2050 with CO₂ levels at about 435 parts per million (ppm), about 20 ppm above today’s (2019) level. After 2050, the forcing trajectory of RCP 2.6 is well below the other RCPs.
- RCP 4.5 (medium-low) assumes large reductions in GHG emissions that are less drastic and take effect later than in RCP 2.6, with CO₂ at about 475 ppm at 2050 and rising. At 2050 the forcing of RCP 4.5 is slightly above RCP 6.0, but after 2070 it levels out so that it is below RCP 6.0.
- RCP 6.0 (medium-high) assumes moderate reductions in emissions, and its forcing is very similar to RCP 4.5 at 2050 and continues to climb throughout the 21st century.

- RCP 8.5 has greater forcing than the other RCPs at 2050, with CO₂ at about 530 ppm, and the gap increases over the second half of the 21st century. By 2100 RCP 8.5 has CO₂ levels around 950 ppm, over double the 2019 level. RCP 8.5 assumes essentially no reduction in emissions.

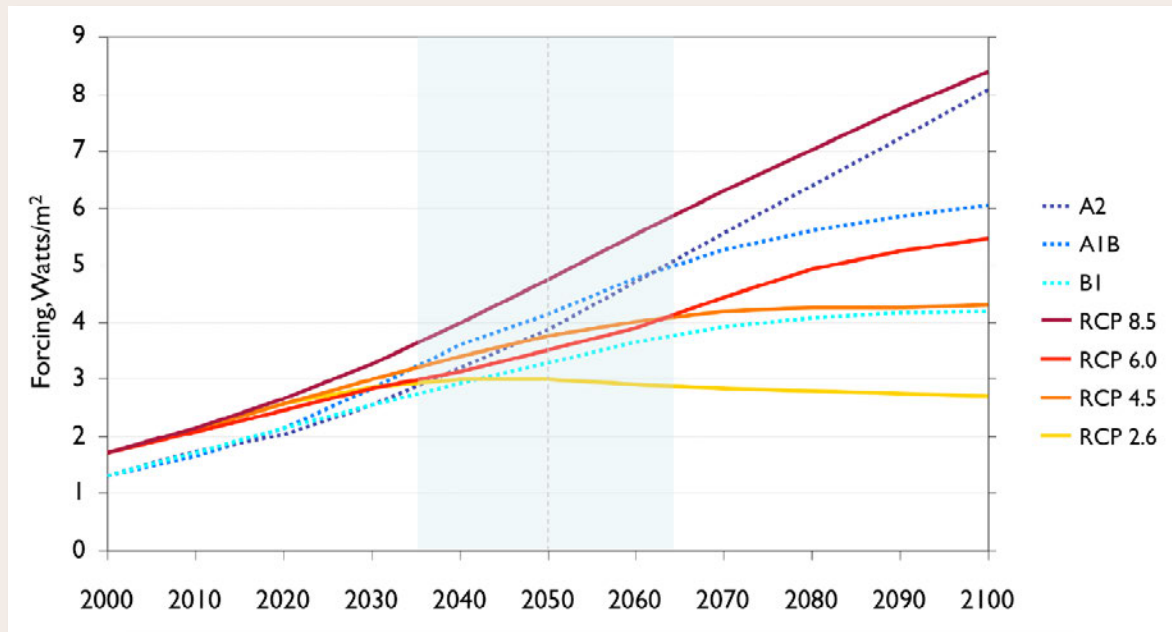


Figure 11.4

Global radiative forcing, 2000–2100, of the four Representative Concentration Pathways (RCPs) used to drive the current-generation (CMIP5) climate models and the three main SRES emissions scenarios used to drive the previous-generation (CMIP3) climate models. The CMIP6 model projections are being driven by slight variants on the four CMIP5 RCPs, along with five other emissions scenarios. (Source: Lukas et al. 2014; Data: SRES: IPCC 2000; RCP: IIASA RCP Database; <http://tntcat.iiasa.ac.at:8787/RcpDb/>)

For CMIP6, in the core future projections (“ScenarioMIP”), the RCPs have been retained, and each will be cross-referenced with an SSP (Societally Significant Pathway). For the CMIP6 projections, the climate forcing trajectories from 2020–2100 of these four RCPs are slightly different than in CMIP5 (Figure 11.3), so precise comparisons between CMIP5 and CMIP6 projections at mid-century are not quite apples to apples, although the climate forcings at end of the century will be the same. The 4 RCP-SSP scenarios are augmented by 5 additional SSP-based emission concentration scenarios which, like the current RCPs, have a specified century-end climate forcing level. These 5 scenarios will fill in the gaps between the 4 current RCPs, with forcings of 1.9, 3.4 (two scenarios), 6.3, and 7.0 W/m², respectively. It is not yet known how many individual GCM projections will be made available from each of the CMIP6 RCP-SSP scenarios.

While the RCPs were intended by their developers to be treated as though they were equally likely to occur, many impact assessments based on CMIP5 GCM output have excluded projections based on RCP2.6, including the forthcoming “Exploring Climate and Hydrology Projections from the CMIP5 Archive” report (Reclamation 2020). The draft report noted that RCP2.6 represents an aggressive global emissions mitigation effort and has no analog among the SRES scenarios. The RCP2.6 trajectory requires the implementation of direct CO₂ capture and removal by the end of the century (van Vuuren et al. 2011).

On the other end of the scale, RCP 8.5 is often called the “business-as-usual” scenario, but it was derived from a larger family of “business-as-usual” scenarios (i.e., policies toward global carbon mitigation are not pursued), and RCP 8.5 tracks higher than most of them. Some researchers argue that a return to coal’s dominance of primary energy supply as assumed in RCP 8.5 is increasingly unlikely (Ritchie and Dowlatabadi 2017). It is more appropriate to call RCP 8.5 a “high-end” business-as-usual scenario. Hausfather and Peters (2020) argue that the RCP8.5 trajectory has become highly unlikely due to recent trends in energy use and emissions, and it should be de-emphasized in impacts assessment.

Regardless of whether GCM data from all RCPs is used for analysis, keeping the GCM data driven by each RCP separate throughout the analysis chain allows one to more clearly identify the differences and uncertainty in the final hydrology output that is due only to the RCP. While there is substantial overlap in the ensembles of Colorado River Basin future streamflow generated using RCP 4.5 and RCP 8.5 projections (Figures 11.12 and 11.13), there are also systematic differences associated with the RCP.

11.5 Downscaling and regional climate projections

Overview of downscaling

The “raw” output from GCMs provides our best estimates of future changes in global circulation patterns and can paint a useful broad-brush picture of changes at the global to sub-continental scales (e.g., Figures 11.8 and 11.9 later in this chapter). But the coarse spatial resolution of GCMs makes the raw output less appropriate for analysis of watershed-scale changes, particularly for precipitation. This is especially true in areas of high topographic relief, such as the western U.S. Because the topography of mountain ranges is highly smoothed in the coarse representation of surface features in GCMs, with too-low elevations at the range crests, GCMs poorly simulate orographic precipitation and snow accumulation, and thus runoff from snowmelt—a critical deficiency in the snowmelt-driven Colorado River Basin. Other processes that control local precipitation and temperature in the basin (Chapter 2), such as land-atmosphere feedbacks,

local slope circulations, convective processes, and regional monsoon circulations, are either poorly simulated by the GCMs or occur at spatial scales smaller than the typical GCM grid box.

To address these and other deficiencies in the GCMs, researchers have developed a number of methods to project regional-scale and local-scale changes in climate, using the raw GCM output as a starting point. These regional climate or *downscaling* methods have two primary purposes: first, to produce realistic daily or monthly sequences of weather and climate over regions such as the Colorado River Basin that can be used to run hydrology models and other impacts models, and second, to understand the regional changes that are likely to take place and the mechanisms behind them. The first is a relatively easy technical problem, for which most downscaling methods are sufficient. The second is a much harder and perhaps more important problem, and it is also difficult to quantify how well the different methods meet this goal.

Regional climate or downscaling methods are typically classified into one of two distinct categories: *dynamical* or *statistical* (Wilby and Wigley 1997). The dynamical approach requires running a higher-resolution regional climate model (RCM) over the domain of interest. This has the benefit of producing future projections that are more firmly grounded in our physical understanding of the processes involved, but at a cost of much higher computational resources. In contrast, statistical downscaling approaches typically require little in the way of total computing time, but they are based purely on statistical relationships among observed climate variables, and may not represent future changes in those variables correctly. The calibration of RCMs requires comparison with observed climate variables, so dynamical downscaling is not entirely free from this issue either.

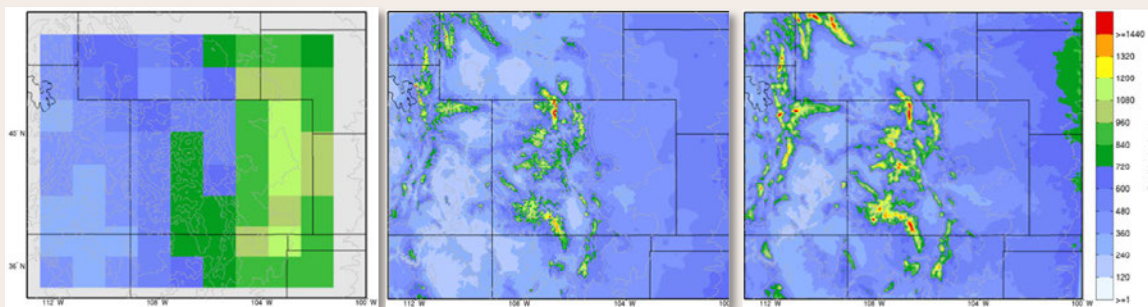


Figure 11.5

Historical average annual precipitation over the Upper Colorado River Basin and adjacent High Plains as simulated by the CESM GCM (100-km grid, left), as estimated by the PRISM observational gridded product (4-km grid, middle), and as simulated by the WRF high-resolution regional weather/climate model (4-km grid, right) which was used to dynamically downscale the CESM GCM simulation on the left.

For the Colorado River Basin, biases in GCMs make raw GCM output data problematic to use directly in hydrology models. Figure 11.5 shows that the mean annual precipitation coming from the Community Earth System Model (CESM; Hurrell et al. 2013), one of the higher-resolution GCMs, is not only of much coarser resolution than the spatial scales represented in the observed climate, it is also heavily biased (i.e., much too wet in the wrong places) and the spatial patterns would not match the spatial patterns of a coarsened observation dataset. In contrast, a very high resolution (4-km) regional climate model simulation using the Weather Research and Forecasting model (WRF; Skamarock and Klemp 2008) reproduces the annual precipitation field of the observations with much better spatial fidelity, and smaller biases. Most statistical downscaling methods also reproduce the observed spatial pattern, but only because they are forced to do so by design, not as a result of accurately simulating the underlying physical processes.

These biases in the GCMs are of critical importance for hydrologic applications. Most obviously, the fact that the GCMs do not properly represent the correct distributions of precipitation and temperature means that a hydrology model run directly with the output of that GCM will not develop a realistic snowpack, and so will not depict the correct magnitude or timing of spring runoff. In essence, such a hydrologic simulation would not be simulating the Colorado River Basin as we know it. That the mountains in a GCM are too low also means that the GCM will not simulate most precipitation in mountainous regions by orographic processes, as it should, but instead is more heavily reliant on simulated convection (i.e., thunderstorms) to generate precipitation. As such, it is possible that the global model would not predict the correct change in precipitation for this region, even if it is predicting the correct change in global circulation (e.g., shift in storm tracks) governing that precipitation. Also, local temperature change signals in the Colorado River Basin are strongly influenced by land surface feedbacks, such as the snow-albedo feedback, that are not present in the GCMs simply because the GCM mountains are not tall enough to maintain a seasonal snowpack in the first place.

Downscaled output variables

The most commonly provided variables from both statistical and dynamical downscaling models are daily precipitation and minimum and maximum temperatures. These variables have been the core of climate projections, in part because observations are available to train statistical methods to predict these variables. In addition, dynamical and quasi-dynamical methods, and some statistical methods, can provide downscaled humidity, shortwave and longwave radiation, and winds, though the lack of widely available observations of these variables means that there has not been as much verification and adjustment to correctly represent these variables.

Requirements for hydrologic modeling

Again, the first task of regional climate projection methods is to produce realistic sequences of weather and climate over regions such as the Colorado River Basin that can be used to run hydrology and other impact models. To be useful for hydrologic modeling, regional climate projections must first provide a high enough spatial and temporal resolution to resolve the hydrologically relevant phenomena. Statistical downscaling methods typically strive for a grid spacing less than or equal to 12 km, and a daily time sequence. A daily weather sequence is often further downscaled temporally to a 1- to 3-hourly sequence based on an idealized diurnal cycle for temperature and radiation, though precipitation often remains at the daily average time scale. This is sufficient to resolve large-scale storm systems, though not the more extreme convective processes (i.e., thunderstorms). The spatial and temporal resolution of a downscaled dataset is also driven by the gridded historical climate data available to train the statistical methods (Chapter 4).

An additional element required for robust hydrologic projections is that the daily to seasonal statistics of the historical regional climate as output from the downscaling method should be consistent with the historical climate data that were used to calibrate the hydrologic model. This can be approached by calibrating the hydrologic model using a dataset that is consistent with the downscaling method, or tuning the downscaling method to be consistent with the dataset that was used to calibrate the hydrologic model. For example, the continental-domain VIC parameters used in many climate projections are semi-calibrated using the Maurer gridded observation product (Maurer et al. 2002) as inputs, and the BCSD downscaled projections described below were trained on the Maurer gridded observations as well (Reclamation 2014).

All hydrologic models require, at a minimum, daily or monthly precipitation and temperature. More sophisticated hydrology and land surface models (Chapter 6) typically require shortwave and longwave radiation, humidity, and wind speed, preferably on an hourly time step. If only daily precipitation and temperature are available, then these additional variables are estimated. This estimation is commonly performed using a set of empirical equations as part of the MT-CLIM algorithm (Running and Thornton 1996); for example, MT-CLIM is embedded in the VIC hydrologic model. MT-CLIM uses a set of calibrated relationships to derive these variables from precipitation and minimum and maximum temperature; however, the viability of these relationships in a future climate has not been thoroughly evaluated. Wind is not estimated by MT-CLIM and is often simply given a climatological average value.

Widely used regional climate downscaling methods and datasets

Many different methods for regional downscaling of GCM output have been developed. The focus below is on those that have been most widely used in impact assessments for water resources and similar applications in the U.S. Publicly available datasets of downscaled projections produced using these methods are summarized in Table 11.3.

Statistical methods

The development of statistical downscaling methods is closely linked with applications in hydrology and water management (Wilby, Hassan, and Hanaki 1998; Wood et al. 2004). Interestingly, these two early works took very different approaches. The Statistical DownScaling Model (SDSM; Wilby, Dawson, and Barrow 2002) uses atmospheric variables that are more robustly simulated by the GCMs, such as humidity and upper-level winds, to predict precipitation.

In contrast, the Bias-Corrected Spatial Disaggregation method (BCSD; Wood et al. 2004) makes use of the GCM precipitation fields, in part because precipitation provides the most direct relationship with hydrologic variables of interest such as runoff (Clark and Hay 2004). More recently constructed analog approaches, including the Locally Constructed Analog method (LOCA; Pierce, Cayan, and Thrasher 2014), have been developed to make use of the spatial patterns of precipitation and temperature simulated by the GCMs to predict changes in regional climate. The focus here is on the two most commonly used statistical methods for water resource applications in the western U.S.: BCSD and LOCA, and also describe key differences between LOCA and two related techniques, BCCA and MACA. In considering any downscaling or regional climate method it is critical to understand the assumptions that the method makes about what information can be used from a GCM.

The statistical downscaling methods used in the United States have mainly been developed through short-term grant-based projects by researchers based at universities, and also at government agencies, often for specific regional applications. Their initial downscaled projection datasets, therefore, may only have regional coverage. An agency-university consortium led by Reclamation later employed the BCSD, BCCA, and LOCA methods to generate new datasets covering the contiguous U.S., facilitating broader use in water resources management and planning.

Table 11.3

Selected widely used and publicly available datasets of downscaled climate projections covering the conterminous U.S. or larger domains that are based on the downscaling methods discussed in this chapter. See the text for references to technical literature describing these methods and datasets. Note that there may be other available datasets produced using the same methods or variants of them. Time step M=monthly, D=daily

Dataset name	Downscaling Method	GCM data	Observed climate data for bias-correction	# Runs	Spatial Resolution	Time step	Associated hydrology-model output available?	Visualization tool that shows these data?
Statistically downscaled datasets								
Reclamation et al. CMIP5 BCSD	Bias-Corrected Spatial Disaggregation	CMIP5; 37 GCMs	Maurer et al. (2002)	231	12 km	M	Yes	No
NASA NEX-DCP30 (in USGS Nat'l Climate Change Viewer)	Bias-Corrected Spatial Disaggregation (variant)	CMIP5; 33 GCMs	PRISM	>100	0.8 km	M	Yes	Yes – USGS National Climate Change Viewer
Reclamation et al. CMIP5 LOCA	Locally Constructed Analogs	CMIP5; 32 GCMs	Livneh et al. (2015)	64	6 km	D	Yes	Yes – NOAA Climate Explorer v2
Reclamation et al. CMIP5 BCCA	Bias-Correction Constructed Analogs	CMIP5; 32 GCMs	Maurer et al. (2002)	134	12 km	D	Yes	No
MACAv2, U. of Idaho (2 variants)	Multivariate Adaptive Constructed Analogs	CMIP5; 20 GCMs	METDATA; Abatzoglou (2013), or Livneh et al. (2013)	40	4 km, or 6 km	D	No	Yes; Climate Toolbox Climate Mapper
Dynamically downscaled datasets								
NARCCAP	Dynamical; 6 RCMs	CMIP3; 4 GCMs	Maurer et al. (2002)	12	50 km	D	No	No
NA-CORDEX	Dynamical; 6 RCMs	CMIP5; 6 GCMs	METDATA; Abatzoglou (2013)	35	25 km or 50 km	D	No	No

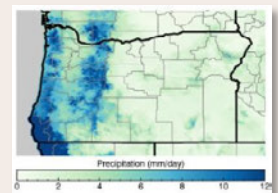
Bias-Corrected Spatial Disaggregation (BCSD). The Bias-Corrected Spatial Disaggregation method (BCSD) has been the most widely used statistical downscaling method in water management in the U.S., including in the Colorado River Basin, due to its longevity and its early adoption (in 2007) by the Reclamation-led consortium. BCSD was developed in the early 2000s to produce regional climate data that are consistent with the observed historical weather and climate, and the long-term, large-scale climate change signal predicted by GCMs. The standard implementation of BCSD uses quantile mapping (Panofsky and Brier 1968) to bias-correct the GCM monthly precipitation and temperature outputs to match an observed gridded climate dataset (e.g., Maurer at 1/8°; see Chapter 4). This bias-corrected dataset is then spatially disaggregated (i.e., downscaled) using historical climatological factors statistically relating each high-resolution (12-km) grid point to the encompassing coarse-resolution value from the GCMs, resulting in monthly downscaled projection values.

A further set of steps is used to generate daily downscaled output, if desired. A projected monthly value as generated in the steps above is used to select a similar month of historical weather from the observed gridded climate dataset, and that sequence of daily weather is rescaled for precipitation, or offset for temperature, to match the monthly values of the downscaled projection dataset. Effectively, this implies that the sequences of monthly precipitation and temperature predicted by the GCM are reasonable and can be relied on, but that the sequences of daily weather from the GCM are not reliable. However, it means that the projected weather sequences under a future climate will not substantially change, even if the underlying GCMs indicate such changes. A variant of BCSD using daily, rather than monthly, GCM data as inputs to produce daily projection data was subsequently applied by Abatzoglou and Brown (2012). This variant method implicitly assumes that the sequences of daily weather from the GCM are in fact reliable.

There have been numerous modifications and variants to the basic BCSD method over time to improve the representation of specific features, including a monthly dataset (NEX-DCP30) produced at 800-m resolution (Thrasher et al. 2013). The details of the most recent implementations of the BCSD by the Reclamation-led consortium can be found in Reclamation (2014).

Users of BCSD are cautioned that in the standard implementations of the method, such as those used by the Reclamation-led consortium, the quantile mapping procedure used for bias correction can alter the GCM-projected future change in precipitation, in a manner that does not appear to be physically meaningful. This issue is described in greater detail below.

National Climate Change Viewer



Link:

<https://www2.usgs.gov/landresources/lcs/nccv/viewer.asp>

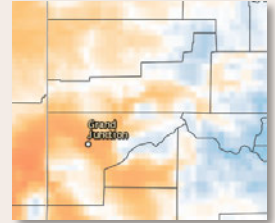
Locally Constructed Analog method (LOCA). The Locally Constructed Analog method (LOCA; Pierce et al. 2015) is a much newer statistical downscaling method that has gained widespread use in the western U.S. in the past several years. LOCA was developed to improve on previous “constructed analog” techniques that all make use of the coarse spatial pattern of the daily weather sequences from GCMs to generate a high-resolution spatial pattern. LOCA uses a very different initial bias-correction step from BCSD, with a frequency-dependent delta-quantile bias correction, similar to that described by Li, Sheffield, and Wood (2010), that corrects not only the statistical distribution, but also the representation on multiple time scales.

Once the bias correction is performed on the coarse scale, LOCA downscales the dataset by finding observed historical analog days with spatial patterns of precipitation or temperature that match the GCM’s coarse resolution spatial patterns. It does this in two steps, and independently for each location; first it selects a collection of, for example, 30 days that match the larger regional pattern (within ~1000 km) around the location to be downscaled, and from those days, LOCA selects the single analog that best matches the more local precipitation or temperature pattern (within ~100 km). The available LOCA dataset used the Livneh et al. (2015) observational dataset on a 1/16° spatial grid to provide a higher spatial resolution dataset than common BCSD products. Unlike BCSD, LOCA assumes that the daily weather sequencing from the GCM is reasonable to begin with. So LOCA permits the daily “weather” to change, and as a result it can change, for example, the average number of storms in a year more than BCSD is likely to.

As with BCSD, more comprehensive overviews of LOCA are available to the reader seeking additional detail on the method (Pierce, Cayan, and Thrasher 2014; Pierce et al. 2015; Reclamation 2016a).

Bias-Corrected Constructed Analog (BCCA) and Multivariate Adaptive Constructed Analog (MACA). BCCA (e.g., Hidalgo, Dettinger, and Cayan 2008) and MACA (Abatzoglou and Brown 2012) are both constructed-analog methods that are conceptually similar to LOCA. In both methods, the selection of the closest analog days is carried out with respect to the entire domain, rather than the LOCA method of selecting analogs at regional-then-local scales. The analog days are then combined by computing weights such that the weighted sum of the analog days best reproduces the GCM-modeled day’s pattern being downscaled, rather than selecting a single best analog day as with LOCA. These same weights are then applied to the original fine-resolution observations from the analog days, producing the final spatially downscaled field. One drawback of BCCA and MACA is that as the domain size increases (e.g., to the contiguous U.S.), it becomes increasingly difficult to find close analog days for the entire

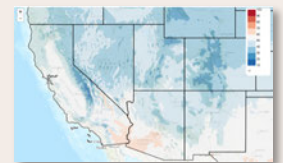
The Climate Explorer



Link:

<https://crt-climate-explorer.nemac.org/>

Climate Mapper



Link:

<https://climatetoolbox.org/tool/climate-mapper>

domain. Also, when downscaling precipitation, it becomes more likely that some of the analog days will have precipitation where the GCM model day has none, which will result in spurious rainfall for that day in the downscaled dataset. Finally, combining multiple analog days over a large domain tends to miss localized extreme precipitation events that occur on a single day, which can influence analyses of the impacts of projected extremes.

Delta method. The simplest statistical downscaling approach is the delta, or period change, method. The delta method starts with time series of historical daily or monthly climate data from gridded observations or from individual stations. The change in the monthly climatological average of temperature between a GCM simulated historical period and GCM projected future period is calculated across the GCM grid. These changes (deltas) are interpolated from the GCM grid down to the observation locations, and then added to the historical observations to produce the downscaled projections. Similarly, the monthly percent change in precipitation from the GCMs is applied to the precipitation observations. The delta method incorporates the coarse-scale patterns of climate change seen in the GCMs while preserving the fine-scale spatial detail and time sequences of weather events from the historical data.

The delta method can also be applied to data that has already been downscaled with another statistical or dynamical method, instead of raw GCM output. This downscaling-and-delta approach was used to generate the climate inputs to the hydrologic models used in the Colorado River Water Availability Study (CWCB 2012) and the Front Range Climate Change Vulnerability Study (Woodbury et al. 2012). The choice of the delta method in these studies indicated a preference for the already observed climate sequences (offset by the GCM-derived deltas) over the future climate sequences that are simulated by the GCMs. The historical sequences are certainly more familiar to stakeholders but cannot capture future changes in climate variability.

Dynamical methods

As with statistical methods, dynamical approaches to regional climate projection have been evolving for over 20 years (Giorgi and Mearns 1991; Leung, Kuo, and Tribbia 2006; Mearns et al. 2013). The general class of models primarily used in dynamical downscaling is referred to as Regional Climate Models (RCMs). RCMs are atmospheric models that run at higher resolutions than GCMs (typically 20–50 km), over a limited domain (i.e., not global). An RCM uses the 3-dimensional atmospheric output from a GCM to supply the conditions at the boundary of the RCM's domain. The RCM then simulates the interior of its domain using fluid dynamics and other equations and physical parameterizations, much like a GCM. One benefit of dynamical downscaling methods is that they involve fewer assumptions

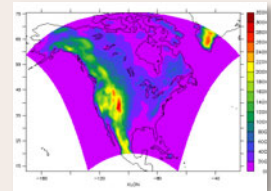
that may become inappropriate in a future climate, such as the assumption, inherent in statistical downscaling, that the historical spatial relationships in climate will not change. But there are still assumptions of climate stationarity embedded in the parameterizations and calibration of RCMs.

Large Regional Domain (NARCCAP and NA-CORDEX). The traditional use of RCMs centers on the idea that an RCM should cover a sufficiently large domain that regional-scale circulation changes are represented, e.g., the North American Monsoon, and that such models should be driven directly with the circulation fields from a GCM to permit changes to regional circulation and weather patterns to be directly represented. This approach was used in the North American Regional Climate Change Assessment Program (NARCCAP; Mearns et al. 2013) and the North American Coordinated Regional Downscaling Experiment (NA-CORDEX; Mearns et al. 2017).

Both NARCCAP and NA-CORDEX employed multiple RCMs to downscale multiple GCMs, with the objective of better understanding the uncertainty in regional climate stemming from both GCMs and RCMs. The NARCCAP RCMs used a grid spacing of approximately 50 km, while the NA-CORDEX RCMs used grid spacings of 50 km and 25 km. While these models provide a better representation of the large-scale regional climate patterns than GCMs, they are not at a sufficient resolution for hydrologic impact assessments in the Colorado River Basin and would require additional statistical bias correction and downscaling. In addition, due to the computational cost of RCMs, these simulations have been performed for many fewer GCMs than in the primary statistical downscaling datasets. NA-CORDEX has downscaled only six GCMs, primarily for the RCP 8.5 scenario. Only three GCMs have been downscaled for RCP 4.5 and only one of those RCM simulations was performed with the higher resolution 25 km grid.

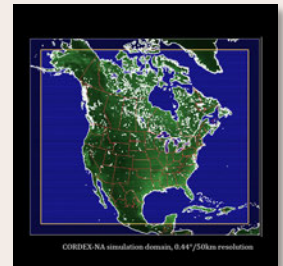
High-resolution convection-permitting and pseudo-global warming (PGW). In addition to the large-domain simulations, very high resolution simulations have been performed for shorter time periods. When atmospheric models use a grid spacing less than about 6 km, they can explicitly model convective processes, without the use of a simplified parameterization. In addition, they represent topography much better. Consequently, these high-resolution models better match observed precipitation and temperature patterns over the Upper Basin (Ikeda et al. 2010; Mahoney et al. 2013; Rasmussen et al. 2014) and over larger domains (Prein et al. 2015; Liu et al. 2017). However, since the computational cost of a model increases with the cube of the decrease in grid spacing, these high-resolution models have an enormous computational cost. Simulations over the contiguous United States using a 4-km grid spacing have been performed, but only over relatively short time periods: 13 years for the historical period and 13 years for the future period (Liu et al. 2017).

North American Regional Climate Change Assessment Program (NARCCAP)



Link:
<https://www.narccap.ucar.edu/>

North American CORDEX Program (NA-CORDEX)



Link:
<https://na-cordex.org/>

Because climate variability's short (decadal) time scales make it hard to discern the forced anthropogenic climate signal, these high-resolution simulations use a different method to evaluate the impacts of climate change, referred to as the Pseudo-Global Warming (PGW) method. The PGW method keeps the weather at the boundaries of the model consistent in current and future climate, but it perturbs those weather patterns with a mean climate change signal in the future climate. This means that these simulations have a warmer, moister background state, and they project what would happen to today's weather in a future climate. As a result, one can look at the differences between two 13-year simulations (current and future) to understand a climate change signal that would otherwise be obtained by comparing two 30-year periods from multiple GCMs, as is typically done. These simulations provide important guidance about the likely mean future climate changes driven by thermodynamic changes to the atmosphere, but they cannot depict climate changes caused by major shifts in weather patterns, such as the location of the storm track over the basin or the frequency of major storms.

Other regional climate downscaling approaches

Alternative approaches have been developed to investigate regional changes that fall somewhere in between the two main categories of downscaling methods, blending aspects of both. These include statistical downscaling methods based on atmospheric drivers and quasi-dynamical methods based on physical understanding.

Statistical methods based on atmospheric circulation indices (Wilby, Dawson, and Barrow 2002; Langousis and Kaleris 2014; Timm, Giambelluca, and Diaz 2015) have the advantage of being both developed to match regional observations (as with other statistical methods), and using output fields from a GCM that might reasonably be expected to be simulated well, such as upper air wind speed, temperature, and humidity. However, the relationships between these upper atmosphere parameters and hydrologically relevant meteorology, e.g., precipitation, are often highly non-linear and not well represented by purely statistical models. In addition, the atmospheric fields used do not have significant spatial variability, and as a result the predicted spatial variability in precipitation, in particular, is often too small and this results in unrealistic hydrologic behavior (Gutmann et al. 2014; Mizukami et al. 2016). Ensemble Generalized Analog Regression Downscaling (En-GARD) is a new statistical method, based on a combination of concepts and techniques (Wilby, Dawson, and Barrow 2002; Clark et al. 2004; Clark and Slater 2006), that aims to provide both realistic spatial patterns of precipitation and linkages to atmospheric variables that are better simulated in the GCM than precipitation.

Quasi-dynamical methods (Georgakakos et al. 2012; Gutmann et al. 2016) solve many of the same equations as full dynamical methods, but make

various simplifications to permit them to run hundreds of times faster than traditional RCMs. For example, the development of the Intermediate Complexity Atmospheric Research model (ICAR; Gutmann et al. 2016) makes use of an analytical approximation to represent the wind field over mountain ranges, and then performs the same physical advection of heat and moisture in a high-resolution domain while using physical parameterizations from the Weather Research and Forecasting model (WRF; Skamarock and Klemp 2008) to model precipitation and the near-surface air temperature. These quasi-dynamical methods are likely to be useful for predicting changes in orographic precipitation and even land surface feedbacks in the Colorado River Basin. Large ensembles of climate projections from these methods are only just now being produced.

Currently, Gutmann and collaborators at NCAR are conducting a study in which they are applying En-GARD and ICAR to CMIP5 projections to produce GCM-informed Colorado River Basin streamflow ensembles, in order to evaluate the results and understand the implications of using these downscaling methods. This work is being funded by Reclamation and the other sponsors of this report.

Uncertainties and knowledge gaps in regional climate downscaling

Regional climate downscaling has many uncertainties associated with it. In particular, any regional climate method is reliant on information from the GCM, to varying degrees, and a regional climate projection can only compensate for some aspects of GCM performance deficiencies (Maraun et al. 2017). In addition, a large number of physical processes known to operate on smaller scales, such as the snow-albedo feedback effect (Letcher and Minder 2015) are not represented in statistical methods and can be clearly demonstrated to alter the climate change signal (Lanzante et al. 2018). Similarly, orographic precipitation is not well represented in GCMs, and it is not clear that statistical methods can meaningfully quantify a precipitation change signal when the underlying GCM simulation is improperly specifying how precipitation is being produced.

In general, dynamical and quasi-dynamical methods are better able to explicitly represent features such as the changing distribution of precipitation over a mountain range as snow changes to rain. However, these physically explicit models require numerous parameters within them, which are themselves uncertain. How fast does a snowflake melt as it falls? How does sub-grid variability in the land surface influence local air temperature?

Other GCM deficiencies may lead to poor regional climate signals, regardless of the downscaling method. In particular, no regional climate method is able to fully correct for GCM errors in the location of the primary mid-latitude storm track, such as over the western U.S., and the

resulting errors in the frequency of storm systems for the region. While some large-domain RCMs may be able to shift the storm track location internally, they are somewhat constrained at the domain boundaries by the GCM conditions that drive the RCM. Of greater concern, if the GCM storm track is in the wrong location, statistical methods can correct the effect of this shift with respect to the historical climate record, but they are not addressing the root cause. If the GCM then predicts a future shift in this incorrectly positioned storm track, then a statistical method may inherit from the GCM a change in precipitation of a different sign than if the actual, correctly located, storm track had shifted in the same way (Maraun et al. 2017). As a result, GCMs should first be evaluated for the large-scale circulation that matters to a given region and application before attempting further regional climate refinements.

Opportunities for improvement

There are three overlapping areas for improving our regional understanding and quantification of the future climate change signal in the Colorado River Basin. The first would be further development and deployment of physically oriented methods for studying and projecting regional climate, whether dynamical, statistical, or hybrid (e.g., ICAR, En-GARD, NA-CORDEX, WRF). Most statistical downscaling methods are perfectly adequate at producing fine-scale climate projections to use as inputs to hydrology models, but they can't add to our understanding of physical processes. Second, clear metrics are needed to evaluate the validity of the future climate change signal predicted by different methods. While multi-decadal future projections cannot be validated against observations in the same manner as weather forecasts, there are ways to assess whether one method produces more physically realistic and plausible climate changes than another. Third, better understanding of what is required for a GCM projection or downscaled regional projection to be meaningful in the basin is needed; if the GCM-simulated historic storm track is shifted far from its actual location, it is likely that neither the GCM simulation nor a downscaled regional projection based on it can be trusted to provide changes in cool-season precipitation for the basin. We also need to identify which aspects of future regional climate changes are more or less predictable, and emphasize the former in vulnerability assessment and planning, and conversely, deemphasize the latter.

11.6 Projected future climate changes for the basin

As noted previously, most of the pertinent spatial and temporal information seen in downscaled GCM output is inherited from the “parent” GCM and is not the result of the downscaling method. While GCMs do struggle with many regional to local-scale details, they do a reasonable job in capturing the important physical phenomena of the climate system that play out

between global and regional scales. By looking at the direct-from-GCM projections first, one can also better discern in what ways the regional projections from different downscaling methods may differ from the underlying GCM simulations.

The sections below look at projected climate *changes*, referring to the differences in the GCM's projections of a variable (temperature or precipitation) between a historical period and a future period.

Projected temperature change (direct from GCMs)

All of the CMIP3 and CMIP5 climate models, under all emissions scenarios, project that the climate of the Colorado River Basin will continue to rapidly warm relative to historical variability. Projected changes in temperature for the western U.S. by the mid-21st century (2041–2070) from CMIP5 climate models under two emissions scenarios (RCP 4.5 and RCP 8.5) are shown in Figure 11.6.

Model ensembles under RCP 8.5 (high emissions scenario) show generally warmer outcomes than under RCP 4.5 (medium-low emissions scenario) due to the higher levels of greenhouse gases and the associated climate forcing. However, within each emissions scenario, the 30+ projections (one from each GCM) differ in the projected magnitude of future warming, and so the respective ranges of the projected warming under the two scenarios overlap considerably. Under RCP 4.5, the basin's annual temperatures are projected to warm by +2.5°F to +5°F by mid-century compared to the late 20th century average. Under RCP 8.5, the basin's annual temperatures are projected to warm by +3.5°F to +6.5°F by mid-century. The projected warming in the warmest 20% of the projections under RCP 4.5 is similar to the median projection under RCP 8.5. Most of the projections under RCP 4.5, and nearly all of the projections under RCP 8.5, show a mid-century climate that is, on average, at least 3°F warmer than the 1971–2000 baseline and thus as warm as or warmer than the warmest individual years in the historical record.

The differences in warming shown by the various projections under each RCP have two primary sources; the first and more important is that the GCMs have different simulated responses to each increment of greenhouse gases (i.e., forced change), and the second is the “noise” of simulated multi-decadal natural (internal) variability in temperature—which, while relatively smaller than the forced change, is still present.

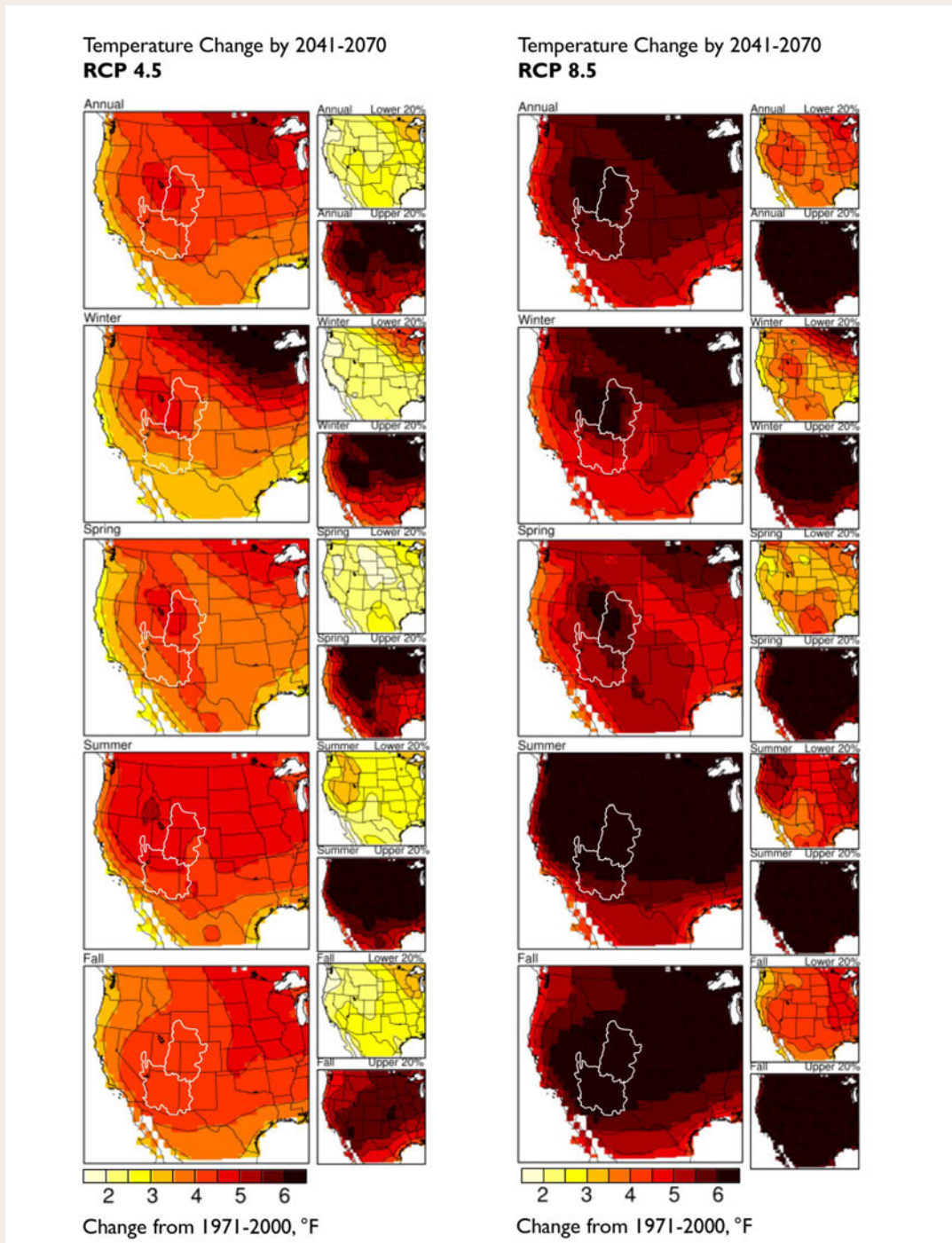


Figure 11.6

Projected annual and seasonal temperature changes by 2041–2070 over the western U.S. from an ensemble of GCMs under RCP 4.5 (left) and RCP 8.5 (right). The large maps show the average change across all of the projections for that RCP ($n=37$; one projection per GCM), and the smaller maps show the averages of the coolest 20% ($n=8$) and warmest 20% ($n=8$) of the projections. (Source: adapted from Lukas et al. 2014. Data: CMIP5 projections re-gridded to 1-degree grid (not downscaled); <http://gdo-dcp.ucllnl.org/>)

Additional features of the projected temperature changes are seen in Figure 11.6. Warming is expected to be slightly greater in summer than the other seasons due to land surface feedbacks; once soils dry out in summer, the energy that had been evaporating soil moisture can instead warm the land surface and the air. The warming is expected to be slightly greater in the Upper Basin compared with the Lower Basin, due to the Upper Basin's greater distance from the oceans' moderation of temperature changes; in fact, the Upper Basin is partly within the "bullseye" of the largest projected warming in the contiguous U.S., which is centered on the northern Great Basin.

Projected precipitation change (direct from GCMs)

The GCMs are in general agreement in projecting a north-south gradient in precipitation change across the western U.S., in which the northern tier of states is expected to see an increase in annual precipitation, and the Southwest is expected to see a decrease in annual precipitation. The Upper Basin sits in the transition area between these two regions, and while the uncertainty about the magnitude of precipitation change is no larger than for other parts of the U.S., there is more uncertainty about the *direction* of change, since the average of the models sits closer to the zero-change line.

Projections of annual and seasonal precipitation change from CMIP5 models under RCP 4.5 and RCP 8.5 are shown in Figure 11.7. On average, the GCMs indicate slight overall tendencies toward higher annual precipitation in the Upper Basin and toward lower annual precipitation in the Lower Basin under both RCP 4.5 and RCP 8.5. Those tendencies are enhanced for the northern half of the Upper Basin (wetter) and the southern half of the Lower Basin (drier). For the Upper Basin, the "wetter" projections call for around 5–10% more annual precipitation, while the "drier" projections call for 5–10% less precipitation. For the Lower Basin, the wetter projections call for 0–5% more annual precipitation, while the drier projections call for 10–15% less precipitation.

The north-south pattern in projected precipitation change across the basin and the West mainly arises because of two mechanisms: the first, *thermodynamic* (i.e., changes in energy states and flows) causes a general global increase in water vapor because the warmer atmosphere is able to hold more moisture (Seager, Naik, and Vecchi 2010). The second, *dynamic* (i.e., changes in atmospheric motions) is a northward shift in the average cool-season storm track across western North America as global atmospheric circulation changes in response to warming, resulting in an expansion of the relatively dry subtropical high-pressure zone that dominates Lower Basin climate (McAfee, Russell, and Goodman 2011; Seager, Naik, and Vecchi 2010).

In the northern tier of the western U.S., where the number of storm systems is projected to remain the same or increase, the increased water vapor leads to greater precipitation; in the far Southwest, the number of such systems is projected to decrease, canceling out the water vapor increase and leading to reduced annual precipitation (USGCRP 2017; McAfee, Russell, and Goodman 2011). The climate models disagree regarding the extent of the northward shift in storm tracks; this disagreement in part leads to their different depictions of future annual precipitation change for the basin, especially the Upper Basin, and other parts of the interior West.

Much of the uncertainty regarding whether annual precipitation will increase or decrease in the Upper Basin reflects inadequate scientific understanding of the expansion of the subtropical dry zone and the net effect of its interaction with the overall wetting of the atmosphere. There is also uncertainty about how ENSO may change in a dramatically warmed climate; greater future tendencies toward El Niño or La Niña would impart additional nudges to the average storm tracks and precipitation patterns.

The GCMs show more pronounced tendencies for change in seasonal precipitation for the basin than annual precipitation (Figure 11.7). In winter (DJF), most models show increased precipitation over the Upper Basin. In spring (MAM), most models show decreased precipitation for the Lower Basin. In summer, while the average change for precipitation for both the Upper and Lower Basins is not large, the “dry” projections show especially large decreases in summer precipitation. However, since the North American Monsoon is not represented well in the GCMs, and the convective storms that dominate summer precipitation cannot be directly simulated by the GCMs, the confidence in the projected changes in summer precipitation is lower than for the other seasons.

The differences in the precipitation change shown by the various projections under each RCP have two primary sources; the first and more important is that the GCMs have different simulated responses to each increment of greenhouse gases (i.e., forced change), and the second is the “noise” of simulated multi-decadal natural (internal) variability in precipitation.

Also important to hydrology and water management is that most of the GCMs project that the variability in precipitation will increase at all time scales over the western U.S., including greater interannual variability (Lukas et al. 2014; Pendergrass et al. 2017). This would mean more frequent occurrence of both very dry and very wet years, and more frequent oscillations from very dry to very wet conditions, such as in 2018–2019, or the reverse, such as in 2011–2012.

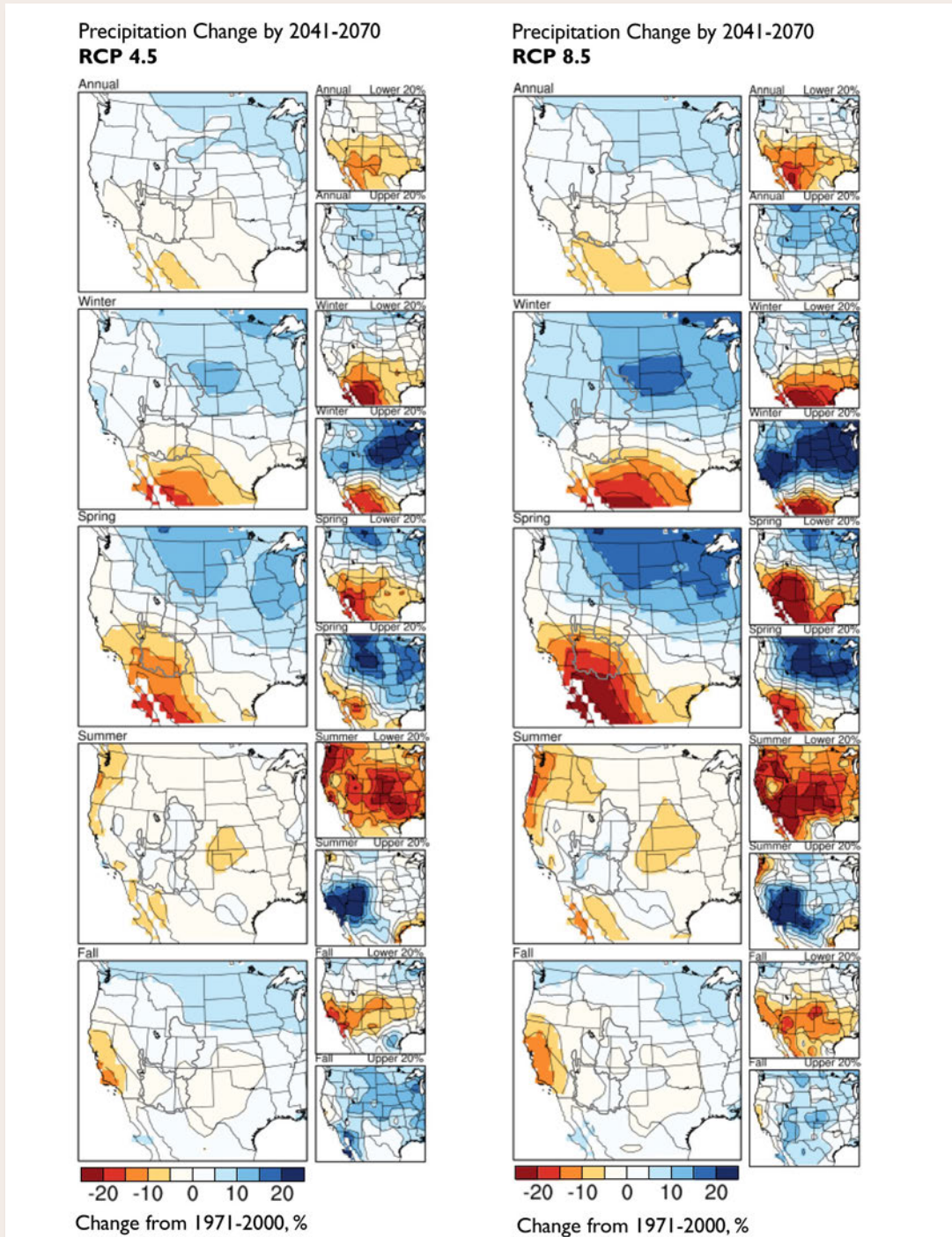


Figure 11.7

Projected annual and seasonal precipitation changes by 2041–2070 over the western U.S. from an ensemble of GCMs under RCP 4.5 (left) and RCP 8.5 (right). The large maps show the average change across all of the projections under that RCP ($n=35$; one projection per GCM), and the smaller maps show the averages of the driest 20% ($n=8$) and wettest 20% ($n=8$) of the model simulations. (Source: adapted from Lukas et al. 2014; Data: CMIP5 projections re-gridded to 1-degree (not downscaled); <http://gdo-dcp.ucllnl.org/>)

The influence of downscaling methods on GCM climate projections

The GCM output is known to have deficiencies that downscaling is intended to correct. As a downscaling method bias-corrects the GCM output and spatially distributes that signal to finer scale, it may alter the GCM's climate change signal, as expressed in future trends. However, the influence of common downscaling methods on the projections of climate change has seldom been systematically examined or quantified. In a review of bias-correction methods, Maraun (2016) asserts that current bias-correction approaches cannot correct GCM-projected trends in a physically plausible manner, and so bias-correction approaches that deliberately preserve the GCM signal should be deployed.

For the Colorado River Basin and the western U.S., a clear example of GCM-signal alteration arose with the monthly BCSD projections based on CMIP3 (e.g., Reclamation 2011; 2012e). The BCSD procedure effectively imparted a “wetting,” so that the bias-corrected and downscaled BCSD data projected larger increases in precipitation than did the underlying GCM projections. When BCSD was later used to downscale the CMIP5 GCM output, this wetting effect was even larger and had a significant influence on the corresponding ensemble of projected hydrologic changes for the Upper Basin (Reclamation 2014; Lukas et al. 2014), as noted in Table 11.3 and in the accompanying text. Maurer and Pierce (2014) found that the BCSD wetting as shown in CMIP5 was in fact due to the quantile mapping (QM) bias-correction procedure within BCSD, and that QM tends to reduce the future trend when the projection has more variability than the observed data, and increase the trend when the model has less variability than the observed data—in other words, the trend alteration appears to be a statistical artifact of the QM procedure. Subsequent analyses of QM in Reclamation (2020) have affirmed the observation that the QM procedure alters projected trends in a manner that is not consistent with physical mechanisms.

Figure 11.8 shows the ensemble mean change in annual precipitation of 10 CMIP5 GCMs that have been downscaled by BCSD as in Reclamation (2014), and by LOCA—which by design does not alter the GCM change signal during bias correction, though it may do so during the spatial downscaling. BCSD shows wetter outcomes (darker blues) in the Upper Basin headwaters and less-dry outcomes (fainter red) in the Lower Basin headwaters than LOCA.

In one of the first comprehensive evaluations of its kind, Alder and Hostetler (2019) compared downscaled projections of temperature and precipitation for the western U.S. generated using 6 different statistical methods, including BCSD (two variants), BCCA, MACA (two variants), and LOCA. The downscaled projections were compared with each other and with the projections from the 14 parent CMIP5 GCMs. They found, first, the

GCM change signals—especially in precipitation—were altered by all of the downscaling methods, with the degree of alteration differing according to region, downscaling method, and the parent GCMs. They found that most of these alterations stemmed from the specific gridded climate dataset (see Chapter 4) used to bias-correct and spatially distribute the GCM output for a particular method (Table 11.3).

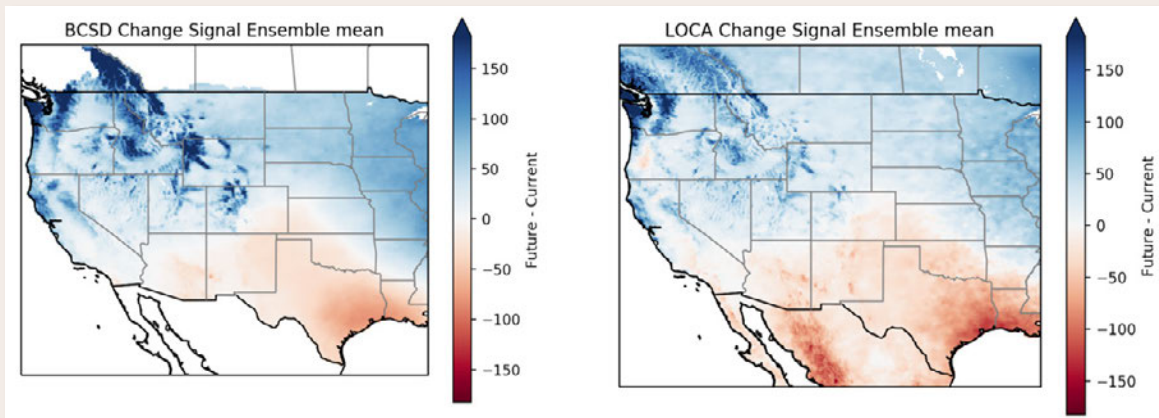


Figure 11.8

Projected percentage change in precipitation for the late 21st century (2070–2099) as averaged across the same set of 10 CMIP5 GCMs under RCP 8.5, using BCSD (left) and LOCA (right) procedures for bias-correction and spatial downscaling. Note that precipitation increases over the Upper Basin headwaters are larger (darker blues) for the BCSD projections. (Source: E. Gutmann, NCAR; Data: <http://gdo-dcp.ucllnl.org/>)

Figure 11.9, from Alder and Hostetler (2019), shows the projected changes in cold-season (October–April) temperature and precipitation for the Upper Basin from the individual 14 GCMs and ensemble of those GCMs, and from the 6 downscaling methods (by individual GCM and the ensemble). The alteration of the GCM cold-season temperature signal by the downscaling method is very small overall except in the case of BCCA, which imparts a clear cooling to the GCM change signal. For precipitation, all 6 downscaling methods impart some wettening to the GCM change signal; the wettening is smallest in MACA-L (MACAv2-Livneh) and in LOCA, while the wettening is largest in the two variants of BCSD.

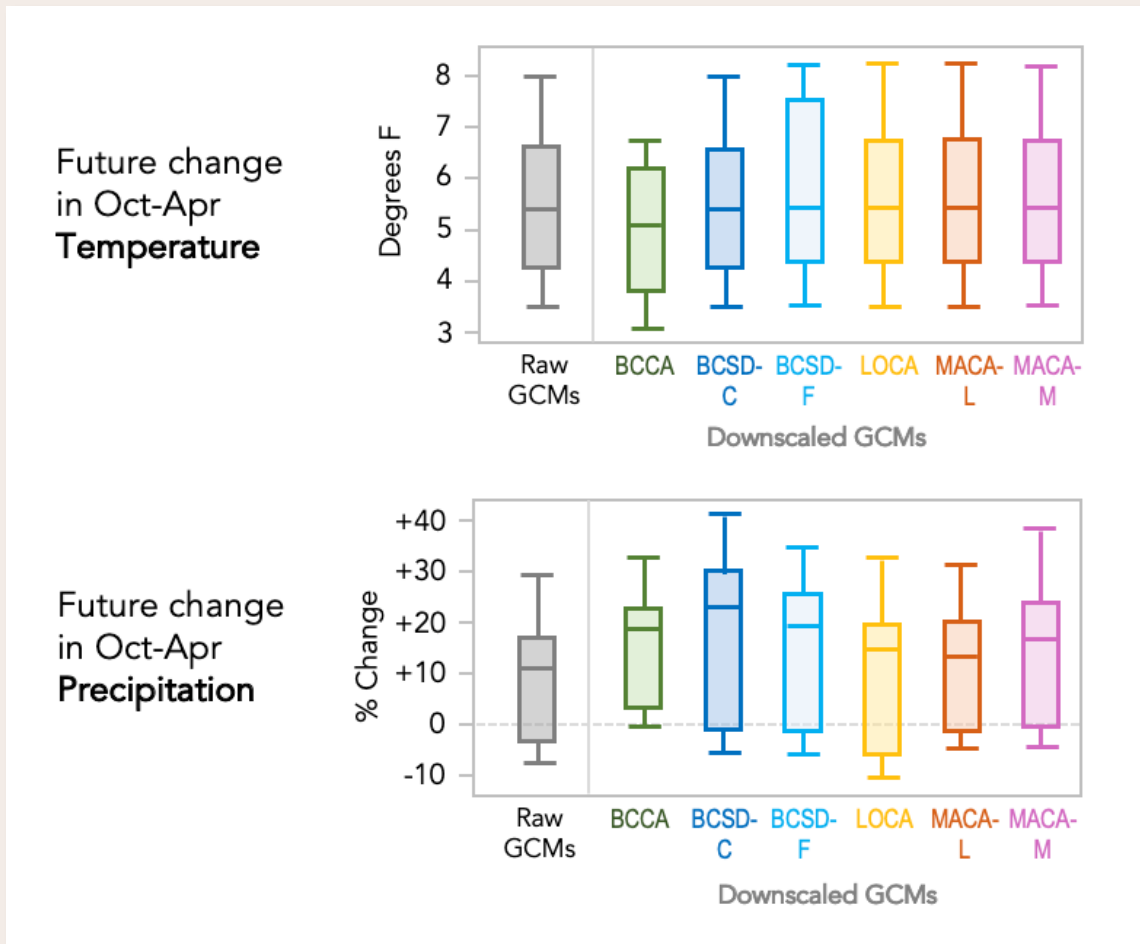


Figure 11.9

Future change (2075–2099 vs. 1950–1999) in average cold season (October–April) temperature (upper) and total precipitation (lower) for the Upper Colorado River Basin under RCP 8.5 shown by 14 “raw” GCM projections (gray) and the corresponding downscaled projections from six statistical downscaling methods (colors). BCSD-C = Reclamation variant of BCSD (Reclamation 2014); BCSD-F = NASA/USGS variant of BCSD (Thrasher et al. 2013); MACA-L = MACAv2-Livneh; MACA-M = MACAv2-METDATA. (Source: adapted from Figure 2 in Alder and Hostetler 2019)

One should keep in mind that these signal alterations and differences between methods are still substantially smaller than the overall range of the GCM-projected changes without downscaling (the black boxplots in Figure 11.9). But they do add another uncertainty to the projections of climate change and hydrologic change for the basin. In most cases, we lack criteria to determine which method(s) and accompanying alterations are the most reliable. For now, users should be cognizant of the uncertainties related to downscaling methods, and researchers will continue to look for better ways to evaluate them, including whether some methods are better suited for some types of applications and their associated impact metrics (e.g.,

hydrologic, ecological) or for certain regions. Some of this applications knowledge has been gleaned by the research community, but it has not been systematically documented.

Projected Upper Basin temperature and precipitation change from a downscaled dataset

Given the discussion above, and recognizing the relative merits of the different available datasets of downscaled GCM data, selecting a representative dataset to examine in greater detail does not imply that it is the best dataset, either in general or for informing water management in the Colorado River Basin. Here the CMIP5-LOCA downscaled projection dataset has been chosen because it contains a broad sample of the full CMIP dataset (32 models, one projection each, under two emissions scenarios, RCP 4.5 and RCP 8.5), it lacks the precipitation ‘wetting’ effect seen in the BCSD datasets, and it is used as the basis for hydrology projections in the forthcoming CMIP5 report (Reclamation 2020) alongside CMIP5-BCSD data. The features of the temperature and precipitation projections that are highlighted below are held in common with nearly all of the statistically downscaled GCM datasets, and are not specific to LOCA.

Figure 11.10 shows the projected Upper Basin temperature change, compared to a 1971–2000 baseline, from CMIP5-LOCA dataset (32 models, one projection each) driven by the RCP 4.5 (top) and RCP 8.5 (bottom) emissions scenarios. A 30-year running average has been applied to the traces to match the typical 30-year analysis period for evaluating future change. To further place the projections in the context of the recent past, the average observed temperature anomaly over the 30-year period 1988–2017 (i.e., the ‘Stress Test’; Chapter 9) is shown; the Upper Basin climate for that period was already 1.1°F warmer than the 1971–2000 baseline.

Just as in the raw GCM output shown earlier, all of the traces show a much warmer future climate, with the magnitude of warming depending on the emissions scenario (the RCP 4.5 and RCP 8.5 ensembles overlap but are clearly different overall), each model’s climate sensitivity (as seen in the spread of the traces under each scenario), and how far out into the future one looks. In general, the projected warming shows a fairly linear response to the respective climate forcing in the emissions scenarios as shown in Figure 11.4; e.g., the RCP4.5 traces tend to flatten out after 2050, just as the forcing in the RCP 4.5 scenario does. Note that while there is some variability (e.g., “bumpiness”) present in the traces, the traces by and large maintain their relative positions over time, indicating that the anthropogenic forced change in temperature is dominant compared to internal (natural) variability at a 30-year timescale.

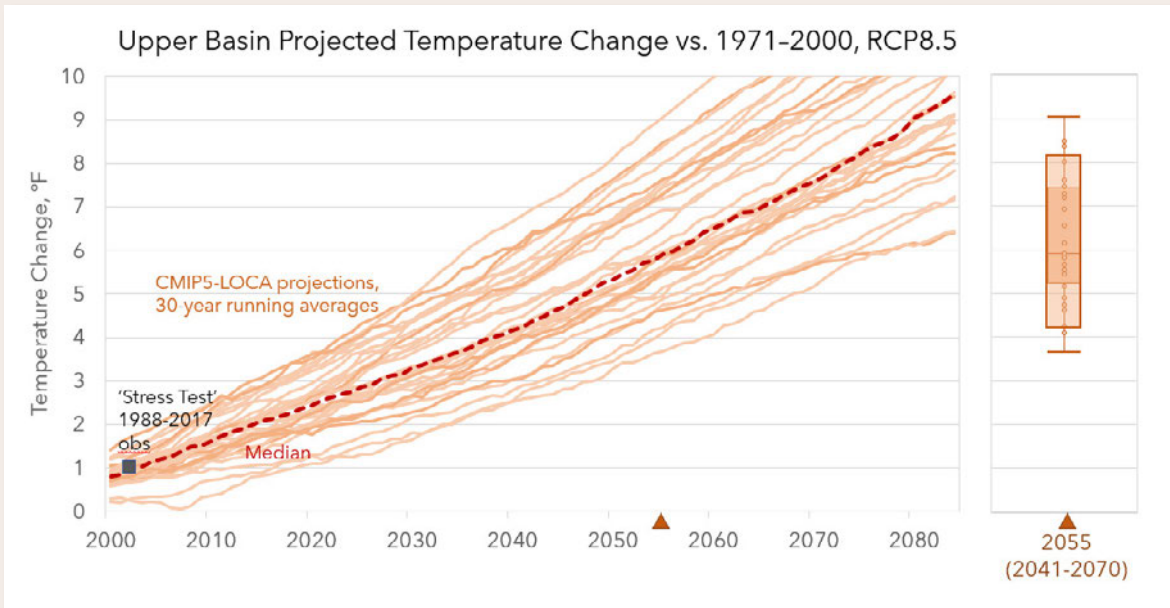
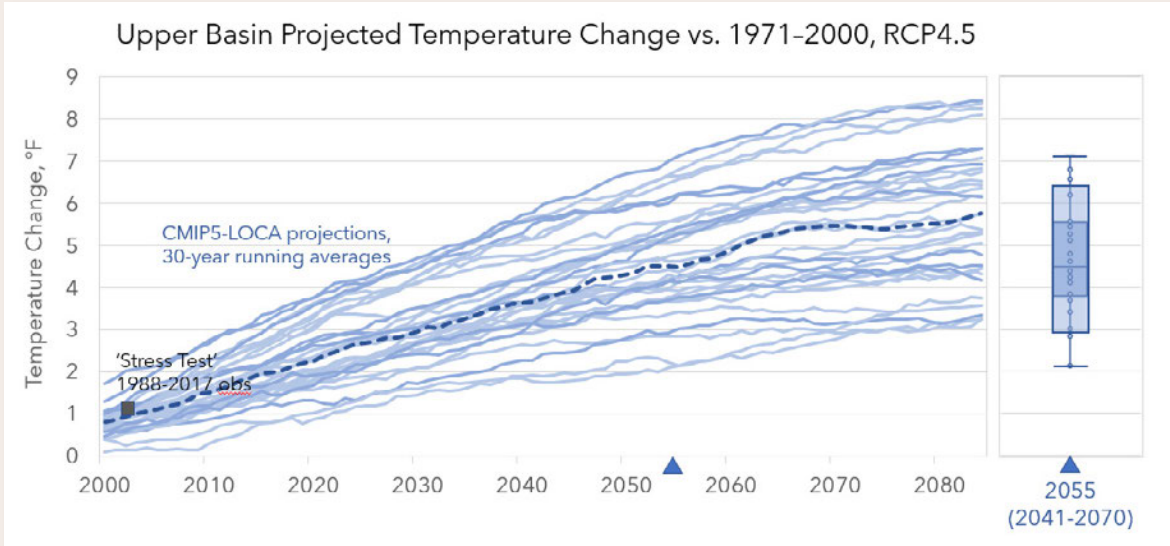


Figure 11.10

Projected future temperature change for the Upper Basin compared to a 1971–2000 baseline, from two ensembles of 32 CMIP5 projections under two emissions scenarios (top: RCP4.5; bottom: RCP8.5) downscaled with LOCA. The lighter traces on both time series plots are the 30-year running averages, plotted on the middle (15th) year, of the projected annual temperature anomaly, with the median trace shown as the dark dashed line. The 30-year average of the observed temperature (“obs”) anomaly over the 1988–2017 ‘Stress Test’ period is shown as a black square. The box-whiskers plots show the distribution of the 30-year average values at 2055 (2041–2070); the outer boxes show the 10th and 90th percentiles; the inner boxes show the 25th, 50th, and 75th percentiles, and the max/min are shown at the ends of the whiskers. (Data: D. Pierce, Scripps Institution; <http://loca.ucsd.edu>; Pierce, Cayan, and Thrasher 2014)

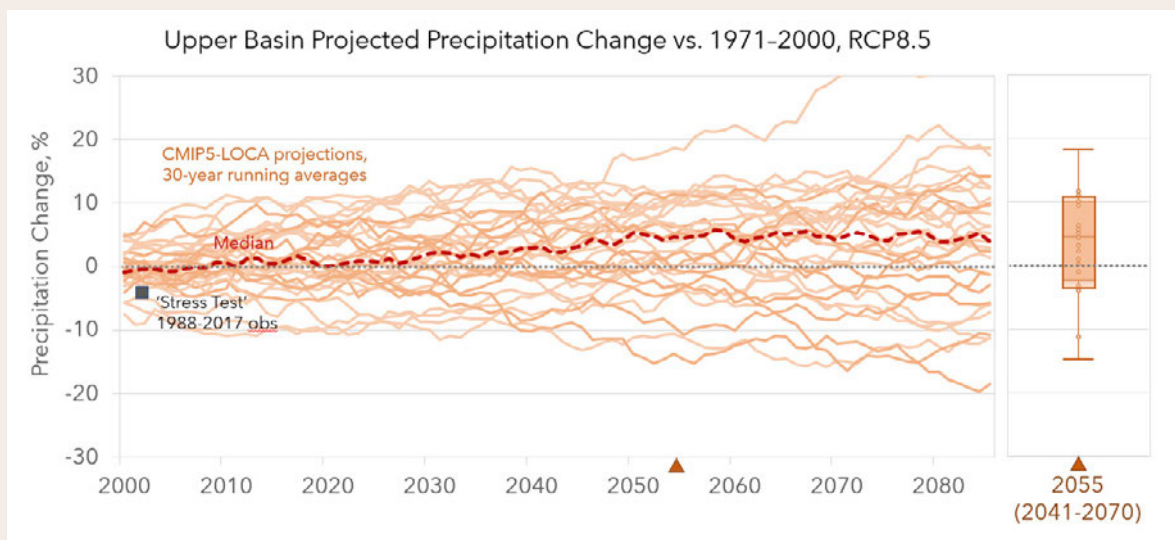
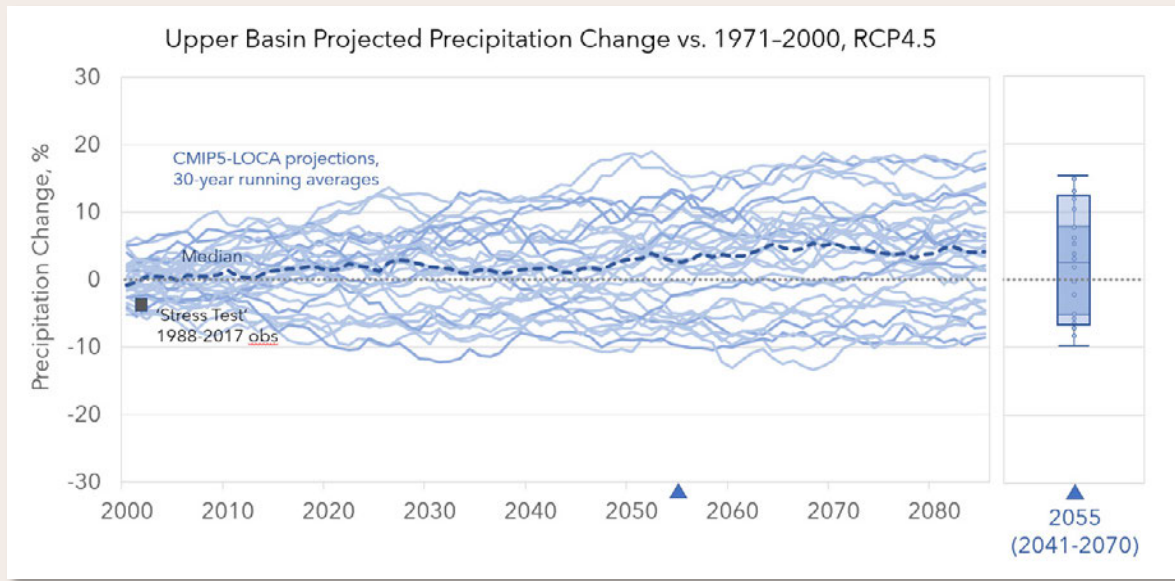


Figure 11.11

Projected future precipitation change for the Upper Basin compared to a 1971–2000 baseline, from two ensembles of 32 CMIP5 projections under two emissions scenarios (top: RCP4.5; bottom: RCP8.5) downscaled with LOCA. The lighter traces on both time-series plots are the 30-year running averages, plotted on the middle (15th) year, of the projected annual precipitation anomaly, with the median trace shown as the dark dashed line. The 30-year average of the observed precipitation (“obs”) anomaly over the 1988–2017 ‘Stress Test’ period is shown as a black square. The box-whiskers plots show the distribution of the 30-year average values at 2055 (2041–2070); the outer boxes show the 10th and 90th percentiles; the inner boxes show the 25th, 50th, and 75th percentiles, and the max/min are shown at the ends of the whiskers. (Data: D. Pierce, Scripps Institution; <http://loca.ucsd.edu>; Pierce, Cayan, and Thrasher 2014)

The magnitudes of projected warming for the 2041–2070 period centered on 2055 are essentially the same as those seen in the raw GCM data and depicted in Figure 11.6. As seen in the box-whiskers plots in Figure 11.10, under RCP 4.5, the vast majority of the projections show warming of +3.0° to +6.5°F by mid-century compared to the late 20th century average, and under RCP 8.5, the vast majority show warming of +4°F to +8°F. As discussed earlier, some climate analysts have suggested that the RCP 8.5 scenario should be de-emphasized due to unrealistic assumptions about future energy supply sources. But note that several of the higher-warming RCP 4.5 traces exceed the median RCP 8.5 level at 2055, and if traces from RCP 6.0 were available from the LOCA dataset, many of them would track at that level too. So even if the RCP 8.5 scenario itself is in fact “very unlikely,” as Hausfather and Peters (2020) asserted, many of the warming outcomes associated with that scenario are also attainable under other RCPs for the same time period.

As discussed earlier in the context of the maps of the raw GCM precipitation output (Figure 11.7), the Upper Basin is located in the transition zone between areas of expected drying (lower annual precipitation) to its south, and expected wetting (higher annual precipitation) to its north. Figure 11.11 shows the projected Upper Basin precipitation change over the 21st century. The average observed precipitation anomaly (-3.5%) during the 30-year ‘Stress Test’ period (1988–2017) is also shown.

The LOCA downscaling procedure by design tries to preserve the GCM-projected trends, and as seen in Figure 11.9 it preserves the GCM’s precipitation trends better than other downscaling methods. So the overall message of the CMIP5-LOCA projections in Figure 11.11 is very consistent with the raw GCM output from CMIP5: there are slight overall tendencies toward higher annual precipitation in the Upper Basin under both RCP 4.5 and RCP 8.5.

But also evident in the time-series plots of Figure 11.11 is a feature that was hidden in the change maps of Figure 11.7, but noted in the text: Multi-decadal internal (natural) variability strongly influences the precipitation traces, manifesting as frequent excursions in the 30-year averages, up and down by 5% or more. These excursions make it hard to discern the long-term trends that might be attributable to forced changes, e.g., changes in atmospheric circulation (ENSO, prevailing storm tracks) or the global moistening of the atmosphere in a warmer climate. To the extent those forced changes are present, they are not leading to significantly different overall changes under RCP 8.5 (which has greater climate forcing) than under RCP 4.5. The ensemble medians throughout the 21st century are very similar, though from 2050 onward the RCP 8.5 has greater spread across the ensemble, perhaps indicating that at least the outlying precipitation

projections are showing greater influence of simulated changes in atmospheric circulation.

Toward the end of the next section, these same LOCA-downscaled projected temperature and precipitation changes will be shown again, after they have been integrated into simulations of future hydrology for the Upper Basin.

11.7 Projections of future Colorado River hydrology under climate change

The future warming projected by all climate models for the Colorado River Basin (Figures 11.6 and 11.10) by itself will have clear impacts on the hydrologic cycle. Most significantly, warming will tend to reduce annual runoff, given the same amount of precipitation. As detailed in previous sections, the magnitude of the warming for any given future period is uncertain, although the progressive nature of the warming means that a slower warming projection will, over more time, still reach thresholds that a faster warming projection reaches earlier. Precipitation, which is the primary determinant of the variability in annual runoff (see Chapter 2), has uncertainty regarding both the direction and magnitude of future change.

The sensitivity of basin runoff to a given temperature change, and to a lesser extent the sensitivity of runoff to a given precipitation change, are also uncertain (Vano, Das, and Lettenmaier 2012; Vano and Lettenmaier 2014; Vano et al. 2014). Together, these uncertainties regarding the magnitude of future temperature and precipitation change, and regarding the true sensitivity of basin hydrology to specific temperature and precipitation changes, have led to a broad range of potential future hydrologic outcomes. However, across the many studies and assessments of future basin hydrology, this range of outcomes is strongly tipped toward reduced runoff, reflecting the pervasive impact of the projected warming.

Methodologies used in past and recent studies

The earliest studies for the basin used empirical statistical relationships to translate basic climate change scenarios (e.g., +2°C warming; -10% precipitation) into basin-scale hydrologic changes, and highlighted the importance of quantifying the sensitivity of runoff to both temperature and precipitation (Stockton and Boggess 1979; Revelle and Waggoner 1983). Later, Nash and Gleick (1991) set what has become a standard for most subsequent studies by deriving specific climate change factors directly from two GCMs and then using a hydrology model (Sac-SMA; Chapters 6 & 8) to translate those climate scenarios into runoff changes for select Upper Basin watersheds.

The modern era of runoff-modeling studies began with Christensen et al. (2004), who pioneered what has become the most prevalent approach (see Figure 11.1 and Table 11.1): a set of GCM projections is statistically downscaled, and the downscaled temperature and precipitation projections are run through a hydrologic model (in their case, and in most later cases, the VIC model; Chapter 6) to obtain future basin streamflows. This same general approach has been followed by many later studies (Table 11.4), with increasingly larger ensembles of GCM projections.

The first analyses of climate change-informed hydrologic simulations for the Colorado River Basin or its headwaters to be formally sponsored by water agencies and to be specific to their long-term water planning appeared in the early 2010s:

- Joint Front Range Climate Change Vulnerability Study (Woodbury et al. 2012)
- Colorado River Water Availability Study, Phase 1 (CWCB 2012)
- West-Wide Climate Risk Assessment (WWCRA; Reclamation 2011)
- Colorado River Basin Water Supply and Demand Study ('Basin Study;' Reclamation 2012e)

These studies exemplified the top-down approach to climate change impact assessment, in which an ensemble of hydrologic simulations is developed from GCMs in order to drive a water system model. All were based on the same set of downscaled GCM climate projections (CMIP3-BCSD), a dataset developed by a consortium including Reclamation and USACE, although the projections were processed differently in each study. The Basin Study (Reclamation 2012e) marked the first basin-scale planning study involving Reclamation that based analyses of future water vulnerability on climate change-informed hydrology. The process of conducting these four studies shed light on several of the key methodological considerations and uncertainties described below and their implications for projecting future changes in basin water supplies. The latter two studies used a larger ensemble of simulations (112 in both cases) that more completely captured the full range of future climatic and hydrologic conditions depicted across the CMIP3 GCMs.

Subsequent assessments have largely focused on updating and refining the ensemble of simulations, by using the next generation of climate models, culling lower-performing climate models, using newer downscaling approaches to assess regional changes, or using different hydrologic models. The update to WWCRA (Reclamation 2016b) used the same approach as the original, but with newer climate models (CMIP5) and a later version of the VIC hydrologic model. Similarly, the forthcoming report, "Exploring Climate and Hydrology Projections from the CMIP5 Archive" (Reclamation 2020) uses CMIP5 climate models, then screening of the

models for performance, a primary downscaling method (BCSD), and also an alternate downscaling method (LOCA).

Results—future changes in annual Upper Basin runoff

Table 11.4 summarizes the results from about 20 studies and assessments since 2005 that have provided estimates of future changes in annual naturalized Upper Basin runoff and streamflow, in nearly all cases as measured at Lees Ferry. For a given methodology, the results from different studies have been similar, and thus the results across the studies are generalized in the “Synthesis of results” column. Looking across the different methodologies, there is broad consistency in two overall findings: 1) most individual simulations within a given study show reduced runoff for the mid-21st century, and 2) the mid-range of the simulations accordingly suggests a reduction in runoff of about 10% to 20%, i.e., down to an average of about 12.0–13.5 maf/year, compared to the historical hydrology of 14.8 maf/year. (There is one exception to these generalizations, as noted below.) Again, the overall tendency toward reduced runoff reflects the pervasive drying effect of the near-certain projected warming, which is either ameliorated by increased precipitation or exacerbated by decreased precipitation, depending on the particular simulation.

Table 11.4

Summary of results from studies since 2005 that have provided estimates of future changes in naturalized Upper Basin runoff. The studies are grouped according to methodology/primary GCM data. Previous summaries of the studies projecting future hydrology for the Upper Basin can be found in Ray et al. (2008); Lukas et al. (2014); and Vano et al. (2014)

Methodology	Studies or assessments using these simulations	Synthesis of results of these studies for Upper Basin runoff in mid-21st century	Comments
CMIP3 GCM projections + BCSD statistical downscaling + hydrologic model	Christensen and Lettenmaier (2007); Reclamation (2011); Woodbury et al. (2012); CWCB (2012); Reclamation (2012e); Harding, Wood, and Prairie (2012); Ficklin, Stewart, and Maurer (2013)	Most (60–80%) simulations show reduced runoff; median change -10% (-25% to +10%)	All studies used the VIC model except Woodbury et al. (Sac-SMA and WEAP)
CMIP3 GCM projections + delta method downscaling + hydrologic model	Deems et al. (2013)	Median change -10% to -20%	Individual simulations not reported; study also examined effects of dust on snow

Methodology	Studies or assessments using these simulations	Synthesis of results of these studies for Upper Basin runoff in mid-21st century	Comments
CMIP3 GCM projections + dynamical downscaling with RCMs; runoff directly from the RCMs	Gao et al. (2011)	Most (2 of 3) simulations show reduced runoff; changes -16% to +5%	Very small projection ensemble; study domain includes Lower Basin headwaters
CMIP3 GCM projections; runoff directly from the GCMs	Milly, Dunne, and Vecchia (2005); Seager et al. (2007)	Nearly all (~95%) simulations show reduced runoff; median change -10% to -20%	This method is less reliable for basin-scale runoff than other methods
CMIP5 GCM projections + BCSD statistical downscaling + hydrologic model	Reclamation (2016b; 2020)	About half of simulations show reduced runoff; median change 0% (-25% to +20%)	Outcomes are shifted wetter than other methods due to the BCSD bias-correction procedure's effects on precipitation
CMIP5 GCM projections + other statistical downscaling + hydrologic model	Alder and Hostetler (2015); Reclamation (2020)	Most (~70%) of simulations show reduced runoff; median change -5 to -10% (-25% to +10%)	Alder and Hostetler (2015) used a variant of BCSD lacking the procedure that leads to wettening; Reclamation (2020) used LOCA
CMIP5 GCM projections + observed runoff sensitivities to temperature and precipitation	Lehner et al. (2019)	All simulations show reduced runoff; median change -17% (-31% to -3%)	Future time period varies by GCM and corresponds to temperature increase of 2°C vs. 1950-2008
CMIP5 GCM projections; runoff changes directly from the GCMs	Seager et al. (2013)	Most (~80%) of simulations show reduced runoff; median change -10% (-30% to +10%)	Results are for the 2021-2040 period; for mid-century, the reductions would be more prevalent and larger
Generalized temperature change from GCMs + hydrologic models (or runoff sensitivity to temperature derived from hydrologic models)	McCabe and Wolock (2007); Udall and Overpeck (2017); Milly and Dunne (2020); Reclamation (2020)	All simulations show reduced runoff; median change -20% (-40% to -5%)	Results only reflect future changes in temperature, not changes in precipitation

There are some appreciable differences in the results among the respective methodologies. The most prominent is that the CMIP5 + BCSO *downscaling + hydrologic model* ensemble reported in recent Reclamation-funded studies (Reclamation 2014; 2016b; 2020) showed wetter (i.e., less dry) outcomes than earlier CMIP3-based hydrologies and CMIP5-based hydrologies produced using different bias-correction and downscaling methods (Alder and Hostetler 2019; Reclamation 2020).

Also, the studies that have analyzed Upper Basin *runoff output directly from* GCMs, whether based on CMIP3 or CMIP5, have found the future runoff reductions to be more prevalent and larger than studies using downscaled climate and hydrology. This shift toward drier outcomes is in part a consequence of the simplified topography in the GCM leading to a smaller or non-existent mountain snowpack.

The last methodology listed (*Generalized temperature change from GCMs + hydrologic model*) shows drier outcomes than other methods, because it only reflects the projected temperature change, and not the precipitation change. Udall and Overpeck (2017), like McCabe and Wolock (2007) a decade previously, argue for separating the impacts on runoff of temperature projections, in which we have very high confidence, from those associated with the much lower-confidence projections of future precipitation.

Finally, the Lehner et al. (2019) study used a novel methodology in which the temperature *and* precipitation changes from CMIP5 GCMs were combined with the respective sensitivities of runoff to temperature and precipitation as statistically derived from observations, creating “observationally constrained” projections of future runoff. All of the individual projections in Lehner et al. (2019) show reductions in streamflow, with magnitudes similar to the temperature-change-only runoff projections in Udall and Overpeck (2017) and similar studies.

Those studies that also include analyses at the sub-basin level consistently indicate a stronger tendency toward decreased runoff for the southern parts of the Upper Basin, including the San Juan River, and less so in the northern parts, including the upper Green River and the Yampa River (Reclamation 2012e; CWC 2012; Alder and Hostetler 2015; Reclamation 2016a; 2020). This north-south gradient in streamflow outcomes is mainly driven by the corresponding north-south gradient in projected annual precipitation, since the projected magnitudes of warming for the different sub-basins are comparable.

As with the downscaled climate datasets, it is difficult to select one representative dataset from the many different analyses of future Upper Basin streamflows to examine in greater detail. Here, a CMIP5-LOCA-VIC dataset of projected streamflows is shown because it matches the CMIP5-

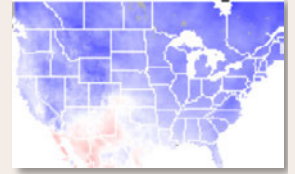
LOCA projections of Upper Basin temperature and precipitation discussed in the previous section, and because a very similar dataset was used in analyses in the forthcoming CMIP5 report (Reclamation 2020). (Note: The LOCA-based projected streamflows shown here in Figures 11.12 and 11.13 are not the same as the LOCA-based projected streamflows that will be available later this year on the [collaborative downscaled climate and hydrology projection archive](#) hosted on Lawrence Livermore National Laboratory's Green Data Oasis; the latter dataset was processed using a different streamflow routing scheme and will have more individual projections.)

Figure 11.12 shows the projected streamflow change at Lees Ferry from CMIP5-LOCA dataset (32 models, one projection each) driven by the RCP4.5 (top) and RCP8.5 (bottom) emissions scenarios. A 30-year running average has been applied to the traces to match the typical 30-year analysis period for evaluating future change. Note that even with this 30-year smoothing, the individual traces show substantial variability, depicting swings in the apparent future change over the course of the 21st century. Nearly all of this variability is driven by the internal (i.e., natural) variability in precipitation, as shown in Figure 11.11. (See also the sidebar on natural variability below.) This means that the precise features of the distribution of the ensemble at any slice in time, e.g., the box-whiskers plots for 2055, are somewhat arbitrary in that they reflect a snapshot of ever-shifting multi-decadal variability as well as the forced anthropogenic change.

Also note that while the median change is negative (i.e. decreasing streamflow) throughout the 21st century under both RCP4.5 and RCP8.5, and many of the individual traces show streamflow decreasing by 10% or more, the ensemble medians remain relatively constant after about 2050 despite increasing projected basin temperatures. This is because the precipitation increases projected by most of the CMIP5 projections, while relatively small in percentage terms, are still large enough to compensate for the progressive effects of warming in about one-third of the streamflow traces. Even so, about 30% of the traces under both RCP4.5 and RCP8.5 show 30-year average flows at 2055 that are less than the average observed streamflow of 13.3 maf (13% below the 1971–2000 average) during the 1988–2017 period used as the “Stress Test” hydrology (Chapter 9).

Downscaled CMIP3 and CMIP5

Climate and Hydrology Projections



Link:

<https://gdo-dcp.ucllnl.org/>

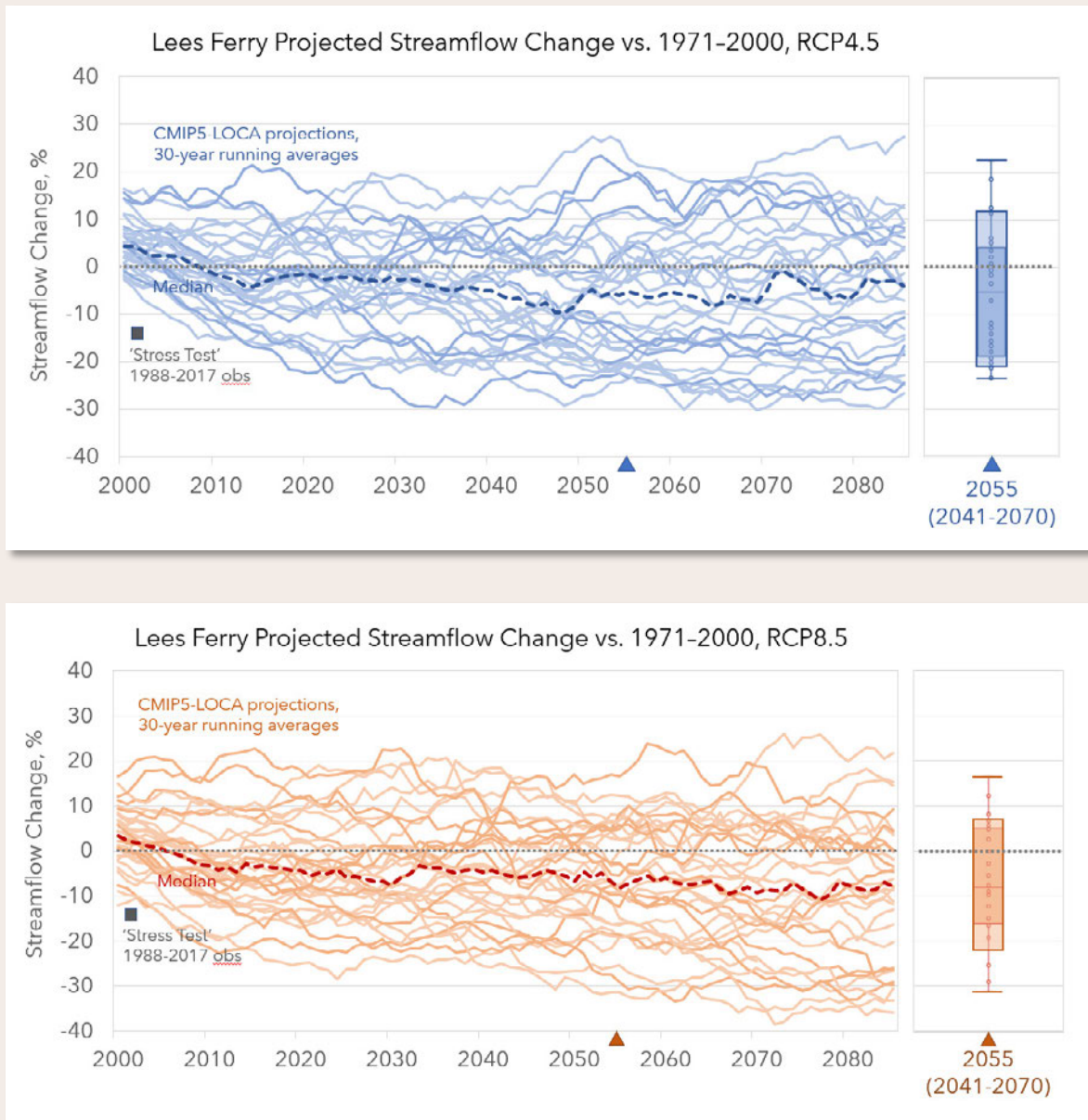


Figure 11.12

Projected future streamflow change at Lees Ferry compared to the 1971–2000 baseline, from two ensembles of 32 CMIP5 projections under two emissions scenarios (top: RCP4.5; bottom: RCP8.5) downscaled with LOCA and run through the VIC model to simulate hydrology. The lighter traces on both time-series plots are the 30-year running averages, plotted on the middle (15th) year, of the projected annual streamflows, with the median trace shown as the dark dashed line. The 30-year average of the 1988–2017 ‘Stress Test’ observed natural streamflow is shown as a black square. The box-whiskers plots show the distribution of the 30-year average values at 2055 (2041–2070); the outer boxes show the 10th and 90th percentiles; the inner boxes show the 25th, 50th, and 75th percentiles, and the max/min are shown at the ends of the whiskers. (Data: N. Mizukami, NCAR)

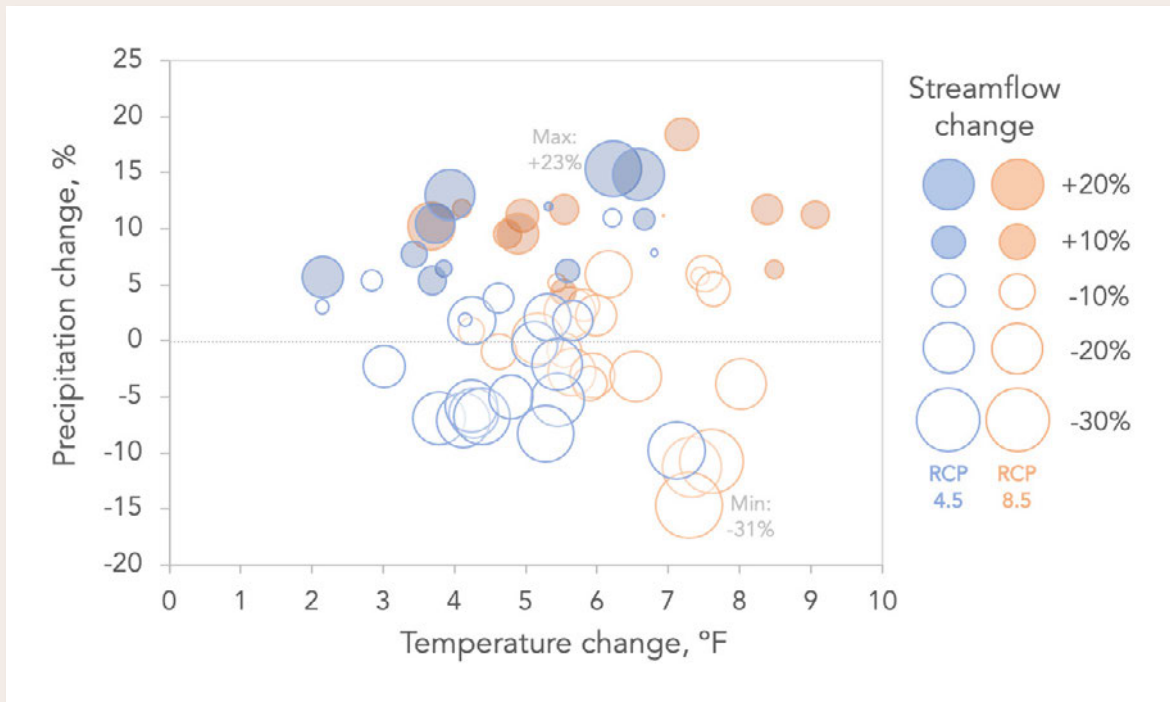


Figure 11.13

Projected future streamflow changes at Lees Ferry for 2041-2070 (2055) relative to the 1971-2000 baseline, and the projected temperature and precipitation changes associated with each projection of streamflow change. About two-thirds of the 64 projections show future decreases in streamflow, many of them despite increases in annual precipitation. These CMIP5-LOCA data are the same as those shown in Figures 11.10-11.12. (Streamflow projection data: N. Mizukami, NCAR; Temperature and precipitation projection data: D. Pierce, Scripps Institution; <http://loca.ucsd.edu>; Pierce, Cayan, and Thrasher 2014)

Figure 11.13 shows the same projected streamflow changes for the 2055-centered period as in the box-whiskers plots in Figure 11.12, but as a function of the projected annual temperature changes (as in Figure 11.10) and the projected annual precipitation changes (as in Figure 11.11). Each circle is an individual CMIP5-LOCA projection (32 under RCP 4.5; 32 under RCP 8.5); filled circles indicate a projected increase in streamflow, while open circles indicate a decrease in streamflow. The size of the circle indicates the magnitude of the change. The position of each circle in the scatterplot shows the projected temperature and precipitation changes associated with that same projection's streamflow change. Across both RCPs, about two-thirds of the projections (42 of 64) show decreasing streamflows, in many cases despite increasing annual precipitation. The largest decreases in streamflow (-20% or more) are associated with moderate or high increases in temperature (>4°F), and decreases in precipitation of 5-15%. Conversely, projected increases in streamflow are only associated with increases in precipitation of 5% or more.



GCM simulation of natural climate variability and implications for streamflow projections

As mentioned earlier in this chapter, GCMs simulate fundamental physical processes within and between thousands of grid cells arrayed across the face of the Earth and vertically up into the atmosphere and down into the oceans. Natural (or “internal”) variability is not “programmed into” these models—it emerges as a consequence of the simulation of physical processes at very short time scales, accumulating into physically realistic behavior of the atmosphere and oceans at longer time scales, including the familiar modes of climate variability such as ENSO.

Each historical simulation or future projection from a GCM contains an expression of internal variability that is unique to that one simulation. GCM simulations over the historical period do not attempt to replicate the actual events and sequences of the observed climate, such as historical wet and dry years as observed in particular regions; however, the events and sequences that are simulated by the GCM over the historical period should be consistent with the statistical characteristics of the historical natural variability. GCM projections of future conditions can and often do show changes in variability relative to the historical period, such as greater interannual variability in precipitation over most regions (Pendergrass et al. 2017).

The simulated internal variability in any one GCM projection—whether over the historical period or a future period—will not be synchronized with the variability seen in projections from other GCMs. If the initial conditions of the atmosphere and ocean at the start of the simulation are varied, even minutely, then projections from the same GCM will develop different variability, due to the sensitivity of the modeled variability on the initial conditions.

As explained in Chapter 2, the observed variability in annual precipitation is much greater than the variability in temperature, relative to long-term observed trends in the two variables. The same is true in future projections: the projected internal variability in precipitation is much greater than that in temperature, relative to the expected anthropogenically forced trends.

This simulated internal variability strongly influences the projections of future hydrologic change in the Colorado River Basin and the way they are interpreted. Harding, Wood, and Prairie (2012) analyzed the large ensemble of 112 CMIP3-based hydrology projections and separately visualized multiple runs that came from a single GCM, which clearly highlights the large role of simulated multidecadal natural variability in the spread of projected streamflow changes for the Upper Basin.

Figure 11.14 shows 17 downscaled projections of Upper Basin annual temperature and precipitation from a single GCM, and 17 traces of VIC-modeled streamflows based on those climate projections. Note that for precipitation, the spread due to internal variability alone is relatively large, and this spread in precipitation is then carried forward into the streamflow traces. The forced trends in precipitation are hard to discern given the internal variability. Temperature, in contrast, has a much clearer forced trend: the traces follow the respective forcing of the emissions scenarios and the forced trend is much larger than the natural variability in temperature. That said, the spread of the temperature traces under each scenario at 2050 is not trivial (roughly 0.5°F–1.5°F).

Analyses of a larger ensemble of projections ($n = 40$) driven by a single emissions scenario from the same GCM (NCAR CCSM3), likewise found that regional changes and trends in temperature and precipitation around the globe are strongly influenced by GCM-simulated natural variability (Deser, Knutti, et al. 2012; Deser, Phillips, et al. 2012). That work and that of Harding, Wood, and Prairie (2012) also indicate that apparent disagreement between different GCMs regarding future regional change can stem from these unaligned and essentially random expressions of multidecadal variability, rather than from different predictions of the future forced change. For example, a “dry” projection of a region of interest from one GCM could be an outlier relative to an overall wet tendency of that GCM if one evaluated a larger set of projections for that region. These large ensembles can also help assess whether the internal variability simulated by the GCMs is similar to the observed variability (McKinnon et al. 2017).

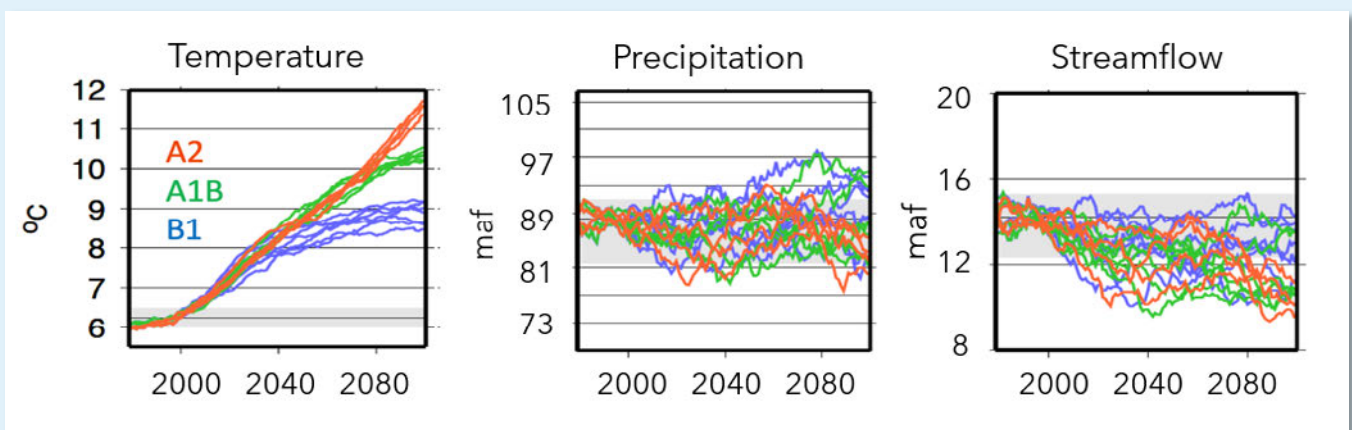


Figure 11.14

Single-GCM (NCAR CCM3) downscaled projections of (left) Upper Basin average annual temperature; (center) Upper Basin average annual precipitation; and (right) annual Colorado River streamflow at Lees Ferry, shown as running 30-year averages plotted on the last year. All 17 projections came from the same GCM, the NCAR CCM3 model, as generated for CMIP3. Projections are color-coded by emissions scenario. Within each emissions scenario (red, green, or blue), the differences among the traces are entirely due to the varying expressions of simulated internal (natural) variability over time. (Source: adapted from Harding, Wood, and Prairie 2012)

Results—future changes in annual Lower Basin runoff

Fewer studies have assessed potential future changes in Lower Basin runoff, that is, tributary flows to the Colorado mainstem. Also, the basin-wide assessments of future hydrology (e.g., Reclamation 2012e) have not reported on projected streamflows for the Lower Basin in the same level of detail as those for Lees Ferry. Studies that have assessed Lower Basin runoff changes, and other datasets that can be readily queried, generally show ranges of future hydrologic projections shifted strongly toward lower streamflows, as in the Upper Basin, but with drier overall outcomes (Table 11.5).

Table 11.5

Summary of results from studies since 2005 that have provided estimates of future changes in Lower Basin runoff. The studies are grouped according to primary GCM data and the methodology.

Methodology	Studies/assessments using these simulations	Results of these studies for Lower Basin runoff in mid-21st century	Comments
CMIP3 GCM projections + BCSD statistical downscaling + hydrologic model (VIC)	Reclamation (2012e)	Mean change for Virgin River, +3%; mean change for Bill Williams River, -4%	
CMIP3 GCM projections; runoff directly from the GCMs	Milly, Dunne, and Vecchia (2005)	Most (~87%) simulations show reduced runoff; median change -20% to -25%	
CMIP5 GCM projections + BCSD statistical downscaling + hydrologic model (VIC)	Reclamation (2020)	Median runoff change for grid boxes in Little Colorado and Salt-Verde headwaters: -10% to -25%	Runoff outcomes for Lower Basin not explicitly given; values here estimated from map of changes
CMIP5 GCM projections + other statistical downscaling + hydrologic model (simple water-balance model)	Alder and Hostetler (2015)	Most (~80%) simulations show reduced runoff; median change -15% (-25% to +10%)	Downscaled data used a variant of BCSD lacking the procedure that leads to 'wetting'

Results—future changes in other hydrologic variables and outcomes

Besides changes in annual runoff volumes, most studies based on datasets of hydrology projections for the basin as cited in Tables 11.4 and 11.5 have also reported future projections of other hydrologic variables, including snowpack, the timing of snowmelt and runoff, and soil moisture. Additional modeling studies have focused on one or more those variables. Below are summaries that generalize the findings of those datasets and studies. In

general, the systematic changes to the hydrology of the basin that have been observed in recent decades, and at least partly driven by the warming trend (Chapter 2), are expected to continue, if not proceed more rapidly than in the past.

Snowpack

As with runoff, the various studies of hydrologic projections for the Upper Basin all show a strong tendency toward future basin-wide declines in April 1 SWE across the individual simulations (Christensen and Lettenmaier 2007; Reclamation 2011; 2012e, 2016b, 2020; Alder and Hostetler 2015), despite projected increases in winter and early spring precipitation in most GCM projections. Additional, snow-focused modeling studies that considered parts or all of the Upper Basin likewise strongly indicate future declines in spring snowpack (Battaglin, Hay, and Markstrom 2011; Lute, Abatzoglou, and Hegewisch 2015). Synthesizing across these studies, the general mid-range of the projected change in April 1 SWE by mid-century is roughly -10% to -20%. As with precipitation and runoff, the southern sub-basins are projected to more likely have declines in April 1 SWE, and larger declines than the northern sub-basins.

This strong tendency seen toward decreased April 1 SWE reflects multiple effects of the projected warming: a shift toward precipitation falling as rain instead of snow, greater sublimation and melt of the snowpack throughout the season, and a shift toward earlier snowmelt in the spring. These warming-related effects are strongly modulated by elevation, with snowpack at higher elevations seeing less impact from warming, as a percentage of current snowpack, than at lower elevations. Analysis of the CMIP5-BCSD hydrology projections also shows a tendency toward decreases in February 1 SWE and March 1 SWE in the Upper Basin, but not as strongly as for April 1 SWE (Lukas et al. 2014). May 1 and June 1 SWE, however, show sharp declines in nearly all of those projections, reflecting a broad shift toward earlier snowmelt.

The future persistence of the snowpack in the Lower Basin headwaters is at much greater risk than in the Upper Basin headwaters, facing larger projected declines in seasonal snowfall or peak SWE or both (Lute, Abatzoglou, and Hegewisch 2015; Christensen and Lettenmaier 2007). This is due to both the greater tendency toward projected declines in cool-season precipitation for the Lower Basin, and also because the current “snow climate” of the headwaters of the Lower Basin is substantially warmer and closer to the critical 0°C (32°F) threshold than in the Upper Basin (Lute, Abatzoglou, and Hegewisch 2015).

These snowpack projections also indicate that in the future, springtime SWE may become a less useful predictor of April–July streamflow and annual streamflow than it is currently (Livneh, Badger, and Lukas 2017).

Regardless of the future change in precipitation, the projected warming means that less of the annual precipitation in the headwaters would fall as snow, and that more of the snowpack would melt and run off prior to April 1, or other benchmark dates, than in the past.

Timing of snowmelt and runoff

The projections of future hydrology for the Upper Basin show much greater agreement regarding future change in the timing of snowmelt and peak runoff timing, and related changes in the annual hydrograph, than future change in annual runoff. Runoff timing is especially sensitive to warming, and nearly all projections, even ones with increased precipitation, show the peak of runoff shifting earlier, with the extent of that warming-driven shift ranging from 1–4 weeks by 2050, depending mainly on the GCM and emissions scenario.

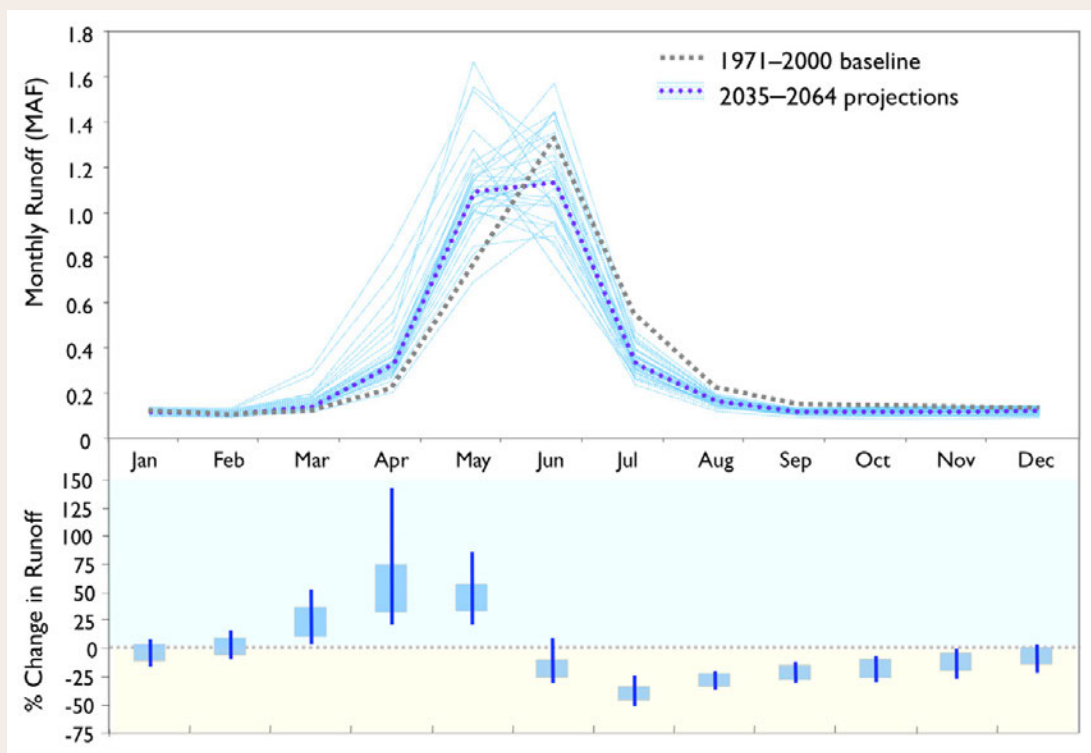


Figure 11.15

Projected monthly runoff change for the Colorado River headwaters for ~2050 (2035–2064) under RCP 4.5, from the CMIP5-BCSD dataset. Top: projected average monthly flows for the 31 projections (light blue lines) and the ensemble median (dark blue dotted line) compared to the 1971–2000 baseline (gray dashed line). Bottom: the corresponding ranges of the monthly runoff changes from that ensemble; the dark blue bars show the range from the 10th to 90th percentile and the light blue boxes show the 25th to 75th percentile. As the hydrograph shifts earlier, March–May runoff increases while June tends to decrease, and July–September runoff sharply decreases in all projections.

(Source: Lukas et al. 2014; Data: http://gdo-dcp.ucllnl.org/downscaled_cmip_projections/)

Figure 11.15 is illustrative of the shift in the annual hydrograph seen in all of the GCM-based future hydrologies for the Upper Basin; here, CMIP5-BCSD projections of monthly runoff for the Colorado headwaters (i.e., at Glenwood Springs) for mid-century under RCP 4.5. That this shift is clearly seen in the CMIP5-BCSD hydrology, which has no overall tendency toward lower streamflow (Table 11.4), indicates how strongly earlier runoff timing is driven by warming temperatures. The shift toward earlier timing manifests as increases in monthly runoff in the spring months (March–May) in nearly all projections, while runoff decreases in summer and early fall (June–September) in nearly all projections, with the largest percentage decline in July. This general seasonal pattern of change is also seen in projections for the other sub-basins of the Upper Basin, as well as for snowmelt-dominated catchments in the Lower Basin.

As discussed in Chapter 2, some portion of the recent observed trend toward earlier runoff in the Upper Basin is due to the effect of dust-on-snow deposition—an effect that has not been explicitly included in the GCM-based studies, with the exception of Deems et al. (2013). If dust-on-snow deposition in the region continues to increase in the future, as it has recently (Clow, Williams, and Schuster 2016), the shift toward earlier runoff in the Upper Basin will occur faster than indicated by the GCM-based hydrology projections (Deems et al. 2013).

Changes in water demand

As stated in the Introduction, this report does not attempt a comprehensive treatment of estimates of water use and projections of future demand. But it is important to note here the projected effects of climate change on water demand, since they may be as significant as future changes in supply in tipping the water balance of the basin toward undesirable outcomes.

In a warmer climate, evaporative demand (i.e., potential evapotranspiration; PET) increases, which would increase the consumption of water by plants—whether in the context of agricultural crops, outdoor municipal vegetation, or phreatophytes—and would also increase evaporation from reservoirs. Estimating the magnitude of the future changes in water use first requires quantifying the PET change given changes in temperature, and then adjusting the temperature-driven changes in PET with changes in precipitation, if any.

The Colorado River Basin Water Supply and Demand Study (Reclamation 2012d) represented PET using the Penman–Monteith method (Chapter 5), both as that method is incorporated within the VIC model, and in separate adjustments for high-elevation areas. That analysis projected that for a 2060-centered period across an ensemble of CMIP3 projections, the

agricultural demand adjustment factor would increase, on average, by 4-10% in 34 VIC grid cells representing important agricultural production areas in all seven basin states. An outdoor municipal demand factor for key urban areas in the basin increased by 4-10%, while reservoir evaporation increased by 3-5%. Nearly all of the changes in the demand factors were driven by temperature, with relatively small adjustments due to projected precipitation change. Basin-wide, the average projected total change in water demand for 2060, driven by climate alone, was an increase of 0.5 maf, with individual projections ranging from no change to an increase in water demand of over 1.0 maf.

The “Exploring Climate and Hydrology Projections from the CMIP5 Archive” study (Reclamation 2020) repeated these analyses across large ensembles of both CMIP3 and CMIP5 projections, for a 2070-centered period. All demand factors were higher under CMIP5 than CMIP3, generally showing an increase of 6-15% for agricultural demand and outdoor municipal demand, over the 1971-2000 baseline. That study did not calculate a basin-wide change in total demand.

The Colorado River Water Availability Study (CRWAS; CWCB 2012), using CMIP3 projections of future temperature and precipitation, calculated changes in agricultural demand (Crop Irrigation Requirement; CIR) for a dozen areas in the Upper Basin in western Colorado. That analysis projected that the average annual CIR would increase by 18-37% for a 2070-centered period. The large discrepancy between the CRWAS results and those summarized above from Reclamation (2012d; 2020) can be attributed to the use of the Blaney-Criddle empirical PET method in the CRWAS analyses, which produces unrealistically large sensitivities of PET to increasing temperature for the higher-elevation sites in the basin (Reclamation 2012d; see also Chapter 5).

11.8 Interpreting climate change-informed hydrology in light of multiple uncertainties

Sources of uncertainty

Reviewing the history of studies of future basin hydrology in Table 11.4, it can be seen that the overall spread of potential future hydroclimatic changes in the Colorado River Basin has not been reduced by the development of new methods and the refinement of climate models—which is also true for global-scale projections of climate and hydrology. In fact, in the last several years, additional sources of uncertainty and error have been identified and more fully appreciated, if not quantified (Clark et al. 2016).

Table 11.6 summarizes the general sources of uncertainty in climate change-informed projections of future hydrology. Until recently, the

construction of the various ensembles of downscaled CMIP3 and CMIP5 projections used in Colorado River Basin planning only reflected the first three sources of uncertainty: emissions scenarios, GCM model structure, and internal (i.e., natural) variability. The magnitude of natural climate variability simulated by the models and its effects on estimates of future change is larger than was understood in the late 2000s (Deser, Phillips, et al. 2012; Harding, Wood, and Prairie 2012), which complicates efforts to identify and tease apart the uncertainties from other sources. The remaining sources of uncertainty in Table 11.6 have not been adequately characterized: the choice of downscaling method and bias-correction method, the choice of observed climate dataset used for bias-correction, and the choice of hydrology model, all of which are key steps in the conventional top-down approach.

The quantifiable contributions of the first three sources to the uncertainty in projections of temperature, precipitation, and runoff for the Upper Basin, from the CMIP5-BCSD ensemble, are depicted in Figure 11.16. In the bottom row, of the total uncertainty in the 30-year average Upper Basin runoff in about 2050, the largest source is the differences among the GCMs (“model”) in simulating the forced change in temperature and precipitation given the same emissions scenario. The second largest source is internal variability manifesting at the 30-year timescale, as also shown in the right-hand panel of Figure 11.14. The smallest source of uncertainty in runoff at 2050 is the choice of emissions scenario.

Interpreting the range of future potential outcomes

The potential future climate and hydrology outcomes for the Colorado River Basin depicted by the large CMIP-based ensembles have created frustration for planners and practitioners, mainly for two related factors. First, the range of projected future outcomes is very broad, with some future hydrologic traces showing significant increases in streamflow, and others showing significant decreases in streamflow. But this range needs to be kept in perspective: even if climate change were not occurring, water managers in the basin would still face large uncertainties about the trajectory of basin hydrology over the next several decades due to natural (internal) variability of the climate system alone, as indicated by the historical hydrology (Chapter 9), paleohydrology (Chapter 10), and ensembles of projections from a single climate model that highlight the magnitude of internal variability (Figure 11.14). Second, the sheer number of traces—often 100 or more—makes data handling, analysis, and interpretation unwieldy.

Table 11.6

Summary of sources of uncertainty in future hydrologic projection based on CMIP GCM runs. The sources in the first three rows are reasonably quantified; see Figure 11.15. T and P refer to temperature and precipitation, respectively.

Source of uncertainty	How this uncertainty can be discerned if not fully characterized	Is this feasible within a typical dataset of CMIP-based hydrologic projections?	Contribution to total uncertainty in projected Upper Basin climate changes	Contribution to total uncertainty in projected Upper Basin runoff changes
Emissions scenario	Look at the differences in the GCM ensemble under different RCPs	Partially— simulated natural variability can confound unless large ensembles from multiple models are available	T: Large P: Small	Small; increases to moderate by 2100
GCM structure and parameters, i.e., representation of key climate processes	Look at results from different GCMs under same RCP	Partially— simulated natural variability can confound unless large ensembles from multiple models are available	T: Large, but decreases by 2100 P: Large	Large
Decadal and multi-decadal natural (internal) variability	Look across multiple runs from a single GCM under the same RCP	Partially— most CMIP GCMs have only 1 run per RCP, but some have multiple runs	T: Small P: Moderate; confounds interpretation of T and P changes	Moderate; decreases toward late 21 st century
Downscaling method (including bias-correction)	Compare results from at least two methods	No— most existing datasets use one or a few very similar methods	<i>Unclear; locally can be large, especially for precipitation</i>	<i>Unclear; locally can be large</i>
Gridded climate data used for statistical downscaling and calibrating RCMs	Compare results using different gridded climate datasets, with all else equal	No— existing datasets use one gridded observational dataset	<i>Unclear</i>	<i>Unclear</i>
Hydrologic model structure and parameters	Compare results using different hydrologic models, with all else equal	No— most datasets use one hydrologic model with one set of parameters	N/A	<i>Unclear; locally can be large</i>

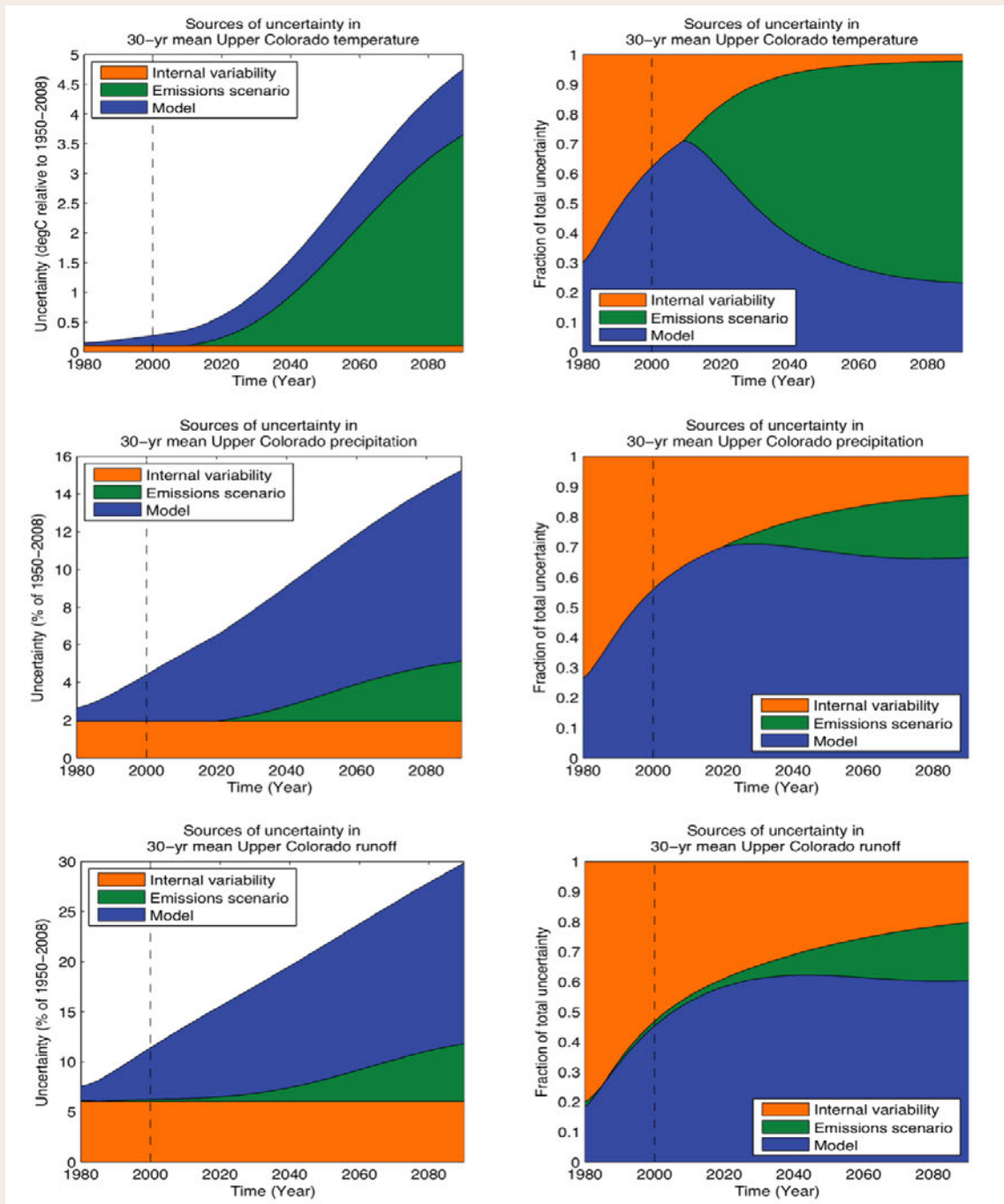


Figure 11.16

Quantification of three key sources of uncertainty (i.e., ensemble spread) in CMIP5 BCSO projections of Upper Basin temperature (upper), precipitation (middle), and runoff (lower): Internal (or natural) variability; Emissions scenario, and Model (GCM) structure and parameters. The left-right pairs of plots show the same data in different ways: (left) the uncertainty associated with each source relative to the observed mean of that variable, and (right) as a fraction of the total uncertainty at that time period. (Source: F. Lehner, NCAR, based on plots by Hawkins and Sutton 2009; Data: <http://gdo-dcp.ucllnl.org/>)

In response to both of these factors, it can be tempting for users to interpret a CMIP-based ensemble of hydroclimate projections in probabilistic terms, e.g., assuming that the mid-point of the ensemble range is more likely than the projections nearer the ends of the range, and focusing on that number. Some judgment of the likelihood of future outcomes is needed in order to allocate resources in most planning paradigms (Schneider 2002). But as noted earlier, the ensembles of GCM projections may be biased by similarity between GCMs stemming from shared development environments and model code. Furthermore, it is believed that even a large ensemble will under-sample the multi-variate space potentially occupied by the future climate; the actual climate may end up outside of the range of the CMIP projections (Stainforth et al. 2007; Shepherd et al. 2018). Accordingly, it should not be automatically *assumed* that the mean or median of the ensemble is the most likely outcome—or that the 90th percentile of the ensemble actually has a 10% likelihood of being exceeded, and so on. Climate researchers have attempted to correct the distributions of regional projected climate change to account for this cross-GCM similarity, though the corrected distributions were even broader, with heavier tails, and the centers of the distributions were often shifted (Steinschneider et al. 2015). Thus, taking the distribution of projected changes (e.g., the box-whiskers plots in Figures 11.10–11.12) at face value as a quantitative measure of future risk is not advisable.

However, this does not mean the distribution of the CMIP ensembles tell us nothing. There is very strong confidence in future warming in general, and that higher emissions scenarios lead to greater warming. The overall shifts in hydroclimate seen in the CMIP-based ensembles—toward lower spring snowpacks, earlier melt and runoff, lower annual runoff volumes, and increasing water demand—are driven largely or almost entirely by the warming. In other words, there are compelling physical mechanisms behind the most relevant hydrologic changes depicted in the ensembles. It is reasonable, then, to take the ensembles as a starting point for exploration of the system consequences.

One way to do this, while also reducing the number of individual traces to deal with when evaluating impacts, is a scenario approach in which several discrete hydroclimate scenarios are created, each based on a carefully selected subset of GCM projections, which cover most of the range or uncertainty across the projections. With only four or five future hydroclimate scenarios, more attention can be given to each pathway. Clark et al. (2016) laid out what they call a “hydrologic storylines” approach in which each storyline is a scenario derived from the traditional top-down methodology, with the collection of storylines representing a sampling of the range of future projections. Reclamation (in an Oklahoma case) and AMEC (CRWAS-II for Colorado; Harding 2015) have also proposed empirical approaches that create a small number of scenarios representing the

spread of the ensemble. A storyline approach, with four future climate scenarios, was also adopted for the 4th California State Climate Assessment (Pierce, Kalansky, and Cayan 2018). An alternative storyline approach proposed by Shepherd et al. (2018) calls for evaluating the changes shown by the different combinations of GCMs, downscaling methods, and hydrology models according to the physical plausibility of the underlying causal mechanisms of these changes. The emphasis is on identifying those modeled future trajectories and changes, such as a northward shift in the typical storm track over the basin, that are linked to the most compelling physics-based and observationally validated explanations. In some cases, this may suggest physically plausible conditions beyond the ensemble range.

Other water system analysts have preferred approaches that keep the CMIP ensemble intact, in all of its diversity and breadth, but begin with the known system vulnerabilities. These bottom-up sensitivity analyses may, for example, create multi-dimensional climate response functions specific to a system outcome, and then plot how the ensemble of climate or hydrologic changes falls across that response surface or response space (e.g., Brown and Wilby 2012).

For now and the foreseeable future, the most reasonable conclusion is that there is no one best approach for addressing uncertainty in projections of future climate. The range and distribution of conditions across the ensemble are biased to an unknown degree, so likelihood should not be directly taken from the distribution—but the ensemble nevertheless contains useful information that should not be ignored.

For further reading and additional guidance on interpreting and applying climate change information in the context of water system planning, Vano et al. (2018) provide a concise and practical primer that also includes a table of additional reading with embedded links.

11.9 Challenges and opportunities

About a decade ago, multiple assessments conducted by, or on behalf of, Reclamation and other water agencies identified research needs and knowledge gaps related to climate change information used in water planning in the Colorado River Basin and the U.S. (Reclamation 2007a; Barsugli et al. 2009; Brekke et al. 2011). Reviewing the findings of these assessments, one is struck by how many of the needs and gaps have persisted over the intervening decade, despite the cumulative investment by the research and practitioner communities.

This is not to say that scientific understanding and technical capacity have not progressed. In particular, there is now much improved availability of

regional climate projection datasets from statistically and dynamically downscaled methods (Table 11.3), and many of these datasets provide daily data that are suitable for analyzing changes in climate extremes. There is also much greater understanding and appreciation, and even quantification, of the different sources of uncertainty in climate change-informed hydrology for the basin. This has included evaluations of different datasets and models (though often not comprehensive enough) for the different steps of the top-down chain.

The list below summarizes several remaining challenges in the development and usability of climate change-informed hydrology, and the opportunities for further improvement in this area. Note that few of these are directed at the research community alone, which indicates that in many cases, the path to greater actionability is not necessarily found in the refinement of models, quantitative methods, or datasets.

Challenge

GCM disagreements in changes of key climate variables: 1) GCMs do not agree on the magnitude of warming to expect globally, or in the basin, for a given emissions scenario-timeframe combination, and 2) GCMs do not agree on the direction and magnitude of annual precipitation change for the basin. Based on past history, further improvements in GCMs (e.g., better resolution of CMIP6 GCMs) will likely only slowly reduce these disagreements.

Opportunities

- Pursue additional guidance beyond the GCM ensemble regarding changes in these uncertain variables, e.g., recent observed trends, climate theory, and expert opinion (e.g., surveys of researchers).
- Identify specific hydroclimate conditions, events, and sequences that lead to vulnerability; there may be greater consensus among the GCMs regarding these than in the changes in annual or seasonal average precipitation, for example.

Challenge

Due to GCM uncertainty and other factors, the range of projected future outcomes for basin hydrology (e.g., change in annual runoff volume at Lees Ferry) from GCM-based ensembles is very broad, and most planning decisions cannot address the full range of potential future conditions without incurring regrets from under- or over-preparation.

Opportunities

- Methods are available (e.g., scenario development, hydrologic storylines) to at least reduce the number of traces from the ensemble, improving their tractability for planning, and potentially identifying more physically plausible and likely outcomes.

- Alternative planning paradigms may be more appropriate for decision making under deep uncertainty. In planning, emphasize those outcomes associated with greater vulnerability and impacts, i.e., drier projections.

Challenge

GCM resolution, while improving, is still coarser than that required for realistic modeling of basin hydrology and system modeling, requiring the application of downscaling methods.

Opportunity

- The HighResMIP experiment within CMIP6 will soon make available an ensemble of GCM projections at 25–50 km resolution. This is still coarser than the resolution optimal for hydrologic modeling but will provide a useful test of what added value can be expected from high-resolution GCMs.

Challenge

Statistically downscaled projection datasets, which dominate applications of regional climate data in water supply assessments, are perfectly adequate as sequences to input in hydrology models, but they add little to our physical understanding of future changes beyond what the GCMs can tell us. The very high resolution of these datasets (1–12 km) can also mislead users as to their accuracy and added value.

Opportunity

- For water supply assessments, look to dynamically downscaled or hybrid methods and datasets (e.g., NA-CORDEX, ICAR, En-GARD) for more physically oriented guidance that can provide context for statistically downscaled datasets, or replace them.

Challenge

The sources of uncertainty and differences in climate change-informed hydrology for the basin have been identified and explored to varying degrees, but not fully examined, including the underlying methodological choices. Thus, data users have incomplete information about uncertainty, and may not be aware of the subjective choices underlying particular results of hydrologic assessments.

Opportunities

- Support comprehensive evaluations of the differences stemming from downscaling methods, bias-correction methods, and hydrologic models.
- Provide visualization tools of future climate and hydrology that are not limited to a single dataset and allow the users to toggle between datasets to clearly see commonalities and differences.

Challenge

Any given ensemble of climate change-informed hydrology (e.g., CMIP5 BCSD) is a complex dataset that is challenging to obtain, analyze, and interpret; the increasing proliferation of similar datasets and their respective underlying methodological approaches can be bewildering to even sophisticated users.

Opportunities

- For both researchers and practitioners, support efforts to provide guidance on the appropriate use of existing datasets, e.g., Vano et al. (2018), and WUCA training workshops.
- Develop and disseminate new methods and datasets only when there is a compelling use case and clear added value over existing datasets.

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Glossary

ablation

The loss of snow from the snowpack due to melting, evaporation, or wind.

absolute error

The difference between the measured and actual values of x .

albedo

The percentage of incoming light that is reflected off of a surface.

aleatory uncertainty

Uncertainty due to randomness in the behavior of a system (i.e., natural variability)

anomaly

A deviation from the expected or normal value.

atmospheric river (AR)

A long and concentrated plume of low-level (<5,000') moisture originating in the tropical Pacific.

autocorrelation

Correlation between consecutive values of the same time series, typically due to time-dependencies in the dataset.

bank storage

Water that seeps into and out of the bed and banks of a stream, lake, or reservoir depending on relative water levels.

bias correction

Adjustments to raw model output (e.g., from a climate model, or streamflow forecast model) using observations in a reference period.

boundary conditions

Conditions that govern the evolution of climate for a given area (e.g., ocean heat flux, soil moisture, sea-ice and snowpack conditions) and can help forecast the future climate state when included in a model.

calibration

The process of comparing a model with the real system, followed by multiple revisions and comparisons so that the model outputs more closely resemble outcomes in the real system.

climate forcing

A factor causing a difference between the incoming and outgoing energy of the Earth's climate system, e.g., increases in greenhouse-gas concentrations.

climatology

In forecasting and modeling, refers to the historical average climate used as a baseline (e.g., "compared to climatology"). Synonymous with climate normal.

coefficient of variation (CV)

A common measure of variability in a dataset; the standard deviation divided by the mean.

consumptive use

The amount of diverted water that is lost during usage via evapotranspiration, evaporation, or seepage and is thus unavailable for subsequent use.

convection

The vertical transport of heat and moisture in the atmosphere, typically due to an air parcel rising if it is warmer than the surrounding atmosphere.

covariate

A variable (e.g., temperature) whose value changes when the variable under study changes (e.g., precipitation).

cross-correlation

A method for estimating to what degree two variables or datasets are correlated.

cumulative distribution function (CDF)

A function describing the probability that a random variable, such as streamflow, is less than or equal to a specified value. CDF-based probabilities are often expressed in terms of percent exceedance or non-exceedance.

Darcy's Law

The mathematical expression that describes fluid flow through a porous medium (e.g., soil).

datum

The base, or 0.0-foot gage-height (stage), for a stream gage.

dead pool

The point at which the water level of a lake or reservoir is so low, water can no longer be discharged or released downstream.

deterministic

Referring to a system or model in which a given input always produces the same output; the input strictly determines the output.

dewpoint

The local temperature that the air would need to be cooled to (assuming atmospheric pressure and moisture content are constant) in order to achieve a relative humidity (RH) of 100%.

dipole

A pair of two equal and opposing centers of action, usually separated by a distance.

discharge

Volume of water flowing past a given point in the stream in a given period of time; synonymous with streamflow.

distributed

In hydrologic modeling, a distributed model explicitly accounts for spatial variability by dividing basins into grid cells. Contrast with **lumped model**.

downscaling

Method to take data at coarse scales, e.g., from a GCM, and translate those data to more local scales.

dynamical

In modeling, refers to the use of a physical model, i.e., basic physical equations represent some or most of the relevant processes.

environmental flow

Water that is left in or released into a river to manage the quantity, quality, and timing of flow in order to sustain the river's ecosystem.

epistemic uncertainty

Uncertainty due to incomplete knowledge of the behavior of a system.

evapotranspiration

A combination of evaporation from the land surface and water bodies, and transpiration of water from plant surfaces to the atmosphere. Generally includes sublimation from the snow surface as well.

fixed lapse rate

A constant rate of change of an atmospheric variable, usually temperature, with elevation.

flow routing

The process of determining the flow hydrograph at sequential points along a stream based on a known hydrograph upstream.

forcing - see **climate forcing** or **weather forcing****forecast**

A prediction of future hydrologic or climate conditions based on the initial (current) conditions and factors known to influence the evolution of the physical system.

Gaussian filter

A mathematical filter used to remove noise and emphasize a specific frequency of a signal; uses a bell-shaped statistical distribution.

gridded data

Data that is represented in a two-dimensional gridded matrix of graphical contours, interpolated or otherwise derived from a set of point observations.

heat flux

The rate of heat energy transfer from one surface or layer of the atmosphere to the next.

hindcast

A forecast run for a past date or period, using the same model version as for real-time forecasts; used for model calibration and to "spin up" forecast models. Same as **reforecast**.

hydraulic conductivity

A measure of the ease with which water flows through a medium, such as soil or sediment.

hydroclimate

The aggregate of climatic and hydrologic processes and characteristics, and linkages between them, for a watershed or region.

hydrograph

A graph of the volume of water flowing past a location per unit time.

hydrometeorology

A branch of meteorology and hydrology that studies the transfer of water and energy between the land surface and the lower atmosphere.

imaging spectrometer

An instrument used for measuring wavelengths of light spectra in order to create a spectrally-resolved image of an object or area.

in situ

Referring to a ground-based measurement site that is fixed in place.

inhomogeneity

A change in the mean or variance of a time-series of data (such as weather observations) that is caused by changes in the observing station or network, not in the climate itself.

Interim Guidelines

The Colorado River Interim Guidelines for Lower Basin Shortages and Coordinated Operations for Lake Powell and Lake Mead, signed by the Secretary of the Interior in December 2007. The guidelines expire in 2026. <https://www.usbr.gov/lc/region/programs/strategies.html>

internal variability

Variability in climate that comes from chaotic and unpredictable fluctuations of the Earth's oceans and atmosphere.

interpolation

The process of calculating the value of a function or set of data between two known values.

isothermal

A dynamic in which temperature remains constant while other aspects of the system change.

jet stream

A narrow band of very strong winds in the upper atmosphere that follows the boundary between warmer and colder air masses.

kriging

A smoothing technique that calculates minimum error-variance estimates for unsampled values.

kurtosis

A measure of the sharpness of the peak of a probability distribution.

lag-1 autocorrelation

Serial correlation between data values at adjacent time steps.

lapse rate

The rate of change of an atmospheric variable, such as temperature, with elevation. A lapse rate is adiabatic when no heat exchange occurs between the given air parcel and its surroundings.

latency

The lag, relative to real-time, for producing and releasing a dataset that represents real-time conditions.

latent heat flux

The flow of heat from the Earth's surface to the atmosphere that involves evaporation and condensation of water; the energy absorbed/released during a phase change of a substance.

Law of the River

A collection of compacts, federal laws, court decisions and decrees, contracts, and regulatory guidelines that apportion the water and regulates the use and management of the Colorado River among the seven basin states and Mexico.

LiDAR (or lidar)

Light detection and ranging; a remote sensing method which uses pulsed lasers of light to measure the variable distances from the sensor to the land surface.

longwave radiation

Infrared energy emitted by the Earth and its atmosphere at wavelengths between about 5 and 25 micrometers.

Lower Basin

The portions of the Colorado River Basin in Arizona, California, Nevada, New Mexico and Utah that are downstream of the Colorado River Compact point at Lee Ferry, Arizona.

lumped model

In hydrologic modeling, a lumped model represents individual sub-basins or elevation zones as a single unit, averaging spatial characteristics across that unit. Contrast with **distributed model**.

Markov chain

A mathematical system in which transitions from one state to another are dependent on the current state and time elapsed.

megadrought

A sustained and widespread drought that lasts at least 10-15 years, though definitions in the literature have varied.

metadata

Data that gives information about other data or describes its own dataset.

mid-latitude cyclone

A large (~500-2000 km) storm system that has a low-pressure center, cyclonic (counter-clockwise) flow, and a cold front. Over the western U.S., **mid-latitude cyclones** almost always move from west to east and are effective at producing precipitation over broad areas.

Minute 319

The binding agreement signed in 2012 by the International Boundary and Water Commission, United States and Mexico, to advance the 1944 Water Treaty between both countries and establish better basin operations and water allocation, and humanitarian measures.

Modoki

An El Niño event that has its warmest SST anomalies located in the central equatorial Pacific; same as "CP" El Niño.

multicollinearity

A condition in which multiple explanatory variables that predict variation in a response variable are themselves correlated with each other.

multiple linear regression

A form of regression in which a model is created by fitting a linear equation over the observed data, typically for two or more explanatory (independent) variables and a response (dependent) variable.

multivariate

Referring to statistical methods in which there are multiple response (dependent) variables being examined.

natural flow

Gaged flow that has been adjusted to remove the effects of upstream human activity such as storage or diversion. Equivalent to **naturalized flow**, **virgin flow**, and **undepleted flow**.

naturalized flow – see *natural flow*

nearest neighbor method

A nonparametric method that examines the distances between a data point (e.g., a sampled value) and the closest data points to it in x-y space ("nearest neighbors," e.g., historical values) and thereby obtains either a classification for the data point (such as wet, dry, or normal) or a set of nearest neighbors (i.e., K-NN).

nonparametric

A statistical method that assumes no underlying mathematical function for a sample of observations.

orographic lift

A process in which air is forced to rise and subsequently cool due to physical barriers such as hills or mountains. This mechanism leads to increased condensation and precipitation over higher terrain.

p

A statistical hypothesis test; the probability of obtaining a particular result purely by chance; a test of statistical significance.

paleohydrology

The study of hydrologic events and processes prior to the instrumental (gaged) record, typically using environmental proxies such as tree rings.

parameterized

Referring to a key variable or factor that is represented in a model by an estimated value (**parameter**) based on observations, rather than being explicitly modeled through physical equations.

parametric

A statistical method that assumes an **underlying mathematical function**, specified by a set of characteristics, or parameters (e.g., mean and standard deviation) for a sample of observations.

persistence

In hydrology, the tendency of high flows to follow high flows, and low flows to follow low flows. Hydrologic time series with persistence are **autocorrelated**.

phreatophytes

Plants with deep root systems that are dependent on water from the water table or adjacent soil moisture reserves.

pluvial

An extended period, typically 5 years or longer, of abnormally wet conditions; the opposite of drought.

principal components regression (PCR)

A statistical technique for analyzing and developing multiple regressions from data with multiple potential explanatory variables.

prior appropriation

"First in time, first in right." The prevailing doctrine of water rights for the western United States; a legal system that determines water rights by the earliest date of diversion or storage for beneficial use.

probability density function (PDF)

A function, or curve, that defines the shape of a probability distribution for a continuous random variable.

projection

A long-term (typically 10-100 years) forecast of future hydroclimatic conditions that is contingent on specified other conditions occurring during the forecast period, typically a particular scenario of greenhouse gas emissions.

quantiles

Divisions of the range of observations of a variable into equal-sized groups.

r

Correlation coefficient. The strength and direction of a linear relationship between two variables.

R²

Coefficient of determination. The proportion of variance in a dependent variable that's explained by the independent variables in a regression model.

radiometer

An instrument used to detect and measure the intensity of radiant energy, i.e., shortwave energy emitted from the sun and reflected by clouds, and longwave energy emitted from the earth's surface.

raster

A digital image or computer mapping format consisting of rows of colored pixels.

reanalysis

An analysis of historical climate or hydrologic conditions that assimilates observed data into a modeling environment to produce consistent fields of variables over the entire period of analysis.

reference evapotranspiration

An estimate of the upper bound of evapotranspiration losses from irrigated croplands, and thereby the water need for irrigation.

regression

A statistical technique used for modeling the **linear relationship** between two or more variables, e.g., snowpack and seasonal streamflow.

relative humidity (RH)

The amount of moisture in the atmosphere relative to the amount that would be present if the air were saturated. RH is expressed in percent, and is a function of both moisture content and air temperature.

remote sensing

The science and techniques for obtaining information from sensors placed on satellites, aircraft, or other platforms distant from the object(s) being sensed.

residual

The difference between the observed value and the estimated value of the quantity of interest.

resolution

The level of detail in model output; the ability to distinguish two points in space (or time) as separate.

spatial resolution - Resolution across space, i.e., the ability to separate small details in a spatial representation such as in an image or model.

temporal resolution - Resolution in time, i.e., hourly, daily, monthly, or annual. Equivalent to time step.

return flow

The water diverted from a river or stream that returns to a water source and is available for consumptive use by others downstream.

runoff

Precipitation that flows toward streams on the surface of the ground or within the ground. Runoff as it is routed and measured within channels is *streamflow*.

runoff efficiency

The fraction of annual precipitation in a basin or other area that becomes runoff, i.e., not lost through evapotranspiration.

sensible heat flux

The flow of heat from the Earth's surface to the atmosphere without phase changes in the water, or the energy directly absorbed/released by an object without a phase change occurring.

shortwave radiation

Incoming solar radiation consisting of visible, near-ultraviolet, and near-infrared spectra. The wavelength spectrum is between 0.2 and 3.0 micrometers.

skew

The degree of asymmetry in a given probability distribution from a Gaussian or normal (i.e., bell-shaped) distribution.

skill

The accuracy of the forecast relative to a baseline "naïve" forecast, such as the climatological average for that day. A forecast that performs better than the baseline forecast is said to have positive skill.

smoothing filter

A mathematical filter designed to enhance the signal-to-noise ratio in a dataset over certain frequencies. Common signal smoothing techniques include moving average and Gaussian algorithms.

snow water equivalent (SWE)

The depth, often expressed in inches, of liquid water contained within the snowpack that would theoretically result if you melted the snowpack instantaneously.

snow course

A linear site used from which manual measurements are taken periodically, to represent snowpack conditions for larger area. Courses are typically about 1,000' long and are situated in areas protected from wind in order to get the most accurate snowpack measurements.

snow pillow

A device (e.g., at SNOTEL sites) that provides a value of the average water equivalent of snow that has accumulated on it; typically the pillow contains antifreeze and has a pressure sensor that measures the weight pressing down on the pillow.

stationarity

The condition in which the statistical properties of the sample data, including their probability distribution and related parameters, are stable over time.

statistically significant

Unlikely to occur by chance alone, as indicated by one of several statistical tests.

stepwise regression

The process of building a regression model from a set of values by entering and removing predictor variables in a step-by-step manner.

stochastic method

A statistical method in which randomness is considered and included in the model used to generate output; the same input may produce different outputs in successive model runs.

stratosphere

The region of the upper atmosphere extending from the top of the troposphere to the base of the mesosphere; it begins about 11–15 km above the surface in the mid-latitudes.

streamflow

Water flow within a river channel, typically expressed in cubic feet per second for flow rate, or in acre-feet for flow volume. Synonymous with **discharge**.

sublimation

When water (i.e., snow and ice) or another substance transitions from the solid phase to the vapor phase without going through the intermediate liquid phase; a major source of snowpack loss over the course of the season.

surface energy balance

The net balance of the exchange of energy between the Earth's surface and the atmosphere.

teleconnection

A physical linkage between a change in atmospheric/oceanic circulation in one region (e.g., ENSO; the tropical Pacific) and a shift in weather or climate in a distant region (e.g., the Colorado River Basin).

temperature inversion

When temperature increases with height in a layer of the atmosphere, as opposed to the typical gradient of temperature decreasing with height.

tercile

Any of the two points that divide an ordered distribution into three parts, each containing a third of the population.

tilt

A shift in probabilities toward a certain outcome.

transpiration

Water discharged into the atmosphere from plant surfaces.

troposphere

The layer of the atmosphere from the Earth's surface up to the tropopause (~11–15 km) below the stratosphere; characterized by decreasing temperature with height, vertical wind motion, water vapor content, and sensible weather (clouds, rain, etc.).

undercatch

When less precipitation is captured by a precipitation gage than actually falls; more likely to occur with snow, especially under windy conditions.

unregulated flow

Observed streamflow adjusted for some, but not all upstream activities, depending on the location and application.

Upper Basin

The parts of the Colorado River Basin in Colorado, Utah, Wyoming, Arizona, and New Mexico that are upstream of the **Colorado River Compact point** at Lee Ferry, Arizona.

validation

The process of comparing a model and its behavior and outputs to the real system, after calibration.

variance

An instance of difference in the data set. In regard to statistics, variance is the square of the standard deviation of a variable from its mean in the data set.

wavelet analysis

A method for determining the dominant frequencies constituting the overall time-varying signal in a dataset.

Acronyms & Abbreviations

24MS

24-Month Study Model

AET

actual evapotranspiration

AgriMET

Cooperative Agricultural Weather Network

AgWxNet

Agricultural Weather Network

AHPS

Advanced Hydrologic Prediction Service

ALEXI

Atmosphere-Land Exchange Inversion

AMJ

April-May-June

AMO

Atlantic Multidecadal Oscillation

ANN

artificial neural network

AOP

Annual Operating Plan

AR

atmospheric river

AR-1

first-order autoregression

ARkStorm

Atmospheric River 1,000-year Storm

ASCE

American Society of Civil Engineers

ASO

Airborne Snow Observatory

ASOS

Automated Surface Observing System

AVHRR

Advanced Very High-Resolution
Radiometer

AWOS

Automated Weather Observing System

BCCA

Bias-Corrected Constructed Analog

BCSD

Bias-Corrected Spatial Disaggregation
(downscaling method)

BCSD5

BCSD applied to CMIP5

BOR

United States Bureau of Reclamation

BREB

Bowen Ratio Energy Balance method

C3S

Copernicus Climate Change Service

CA

Constructed Analogues

CADSWES

Center for Advanced Decision Support for
Water and Environmental Systems

CADWR

California Department of Water Resources

CanCM4i

Canadian Coupled Model, 4th generation
(global climate model)

CBRFC

Colorado Basin River Forecast Center

CCA Canonical Correlation Analysis	CMIP Coupled Model Intercomparison Project (coordinated archive of global climate model output)
CCSM4 Community Climate System Model, version 4 (global climate model)	CNRFC California-Nevada River Forecast Center
CDEC California Data Exchange Center	CoAgMET Colorado Agricultural Meteorological Network
CDF cumulative distribution function	CoCoRaHS Community Collaborative Rain, Hail and Snow Network
CESM Community Earth System Model (global climate model)	CODOS Colorado Dust-on-Snow
CFS Climate/Coupled Forecast System	CONUS contiguous United States (the lower 48 states)
CFSv2 Coupled Forecast System version 2 (NOAA climate forecast model)	COOP Cooperative Observer Program
CHPS Community Hydrologic Prediction System	CP Central Pacific
CIMIS California Irrigation Management Information System	CPC Climate Prediction Center
CIR crop irrigation requirement	CRB Colorado River Basin
CIRES Cooperative Institute for Research in Environmental Sciences	CRBPP Colorado River Basin Pilot Project
CLIMAS Climate Assessment for the Southwest	CRPSS Continuous Ranked Probability Skill Score
CLM Community Land Model	CRSM Colorado River Simulation Model
CM2.1 Coupled Physical Model, version 2.1 (global climate model)	CRSP Colorado River Storage Project

CRSS Colorado River Simulation System	DHSVM Distributed Hydrology Soil Vegetation Model
CRWAS Colorado River Water Availability Study	DJF December-January-February
CSAS	
CRWAS Center for Snow and Avalanche Studies	DMDU Decision Making Under Deep Uncertainty
CTSM Community Terrestrial Systems Model	DMI Data Management Interface
CU consumptive use	DOD Department of Defense
CUL consumptive uses and losses	DOE Department of Energy
CV coefficient of variation	DOW Doppler [radar] on Wheels
CVP/SWP Central Valley Project/State Water Project	DRI Desert Research Institute
CWCB Colorado Water Conservation Board	DTR diurnal temperature range
CWEST Center for Water, Earth Science and Technology	EC eddy-covariance method
DA data assimilation	EC Environment Canada
Daymet v.3 daily gridded surface meteorological data	ECCA ensemble canonical correlation analysis
DCP Drought Contingency Plan	ECMWF European Centre for Medium-Range Weather Forecasts
DEM digital elevation model	EDDI Evaporative Demand Drought Index
DEOS Delaware Environmental Observing System	EFAS European Flood Awareness System

EIS
Environmental Impact Statement

En-GARD
Ensemble Generalized Analog Regression
Downscaling

ENSO
El Niño-Southern Oscillation

EOF
empirical orthogonal function

EP
Eastern Pacific

ERC
energy release component

ESI
Evaporative Stress Index

ESM
coupled Earth system model

ESP
ensemble streamflow prediction

ESRL
Earth System Research Laboratory

ET
evapotranspiration

ET₀
Reference (crop) evapotranspiration

EVI
Enhanced Vegetation Index

FAA
Federal Aviation Administration

FAWN
Florida Automated Weather Network

FEWS
Famine Early Warning System

FEWS
Flood Early Warning System

FIRO
forecast-informed reservoir operations

FLOR
Forecast-oriented Low Ocean Resolution
(global climate model)

FORTTRAN
Formula Translation programming
language

FPS
Federal Priority Streamgages

FROMUS
Forecast and Reservoir Operation Modeling
Uncertainty Scoping

fSCA
fractional snow covered area

FWS
U.S. Fish and Wildlife Service

GCM
global climate model, or general circulation
model

GEFS
Global Ensemble Forecast System

GEM
Global Environmental Multiscale model

GEOS
Goddard Earth Observing System (global
climate model)

GeoTiff
Georeferenced Tagged Image File Format

GFDL
Geophysical Fluid Dynamics Laboratory

GFS Global Forecast System model	HDA hydrologic data assimilation
GHCN Global Historical Climatology Network	HDSC Hydrometeorological Design Studies Center
GHCN-D Global Historical Climate Network-Daily	HEFS Hydrologic Ensemble Forecast Service
GHG greenhouse gas	HESP Hierarchical Ensemble Streamflow Prediction
GIS geographic information system	HL-RDHM Hydrologic Laboratory-Research Distributed Hydrologic Model
GLOFAS Global Flood Awareness System	HMT Hydromet Testbed
GLOFFIS Global Flood Forecast Information System	HP hydrological processor
GOES Geostationary Operational Environmental Satellite	HRRR High Resolution Rapid Refresh (weather model)
GRACE Gravity Recovery and Climate Experiment	HSS Heidke Skill Score
GRIB gridded binary or general regularly-distributed information in binary form	HTESSEL Land-surface Hydrology Tiled ECMWF Scheme for Surface Exchanges over Land
gridMET Gridded Surface Meteorological dataset	HUC Hydrologic Unit Code
GSSHA Gridded Surface/Subsurface Hydrologic Analysis	HUC4 A 4-digit Hydrologic Unit Code, referring to large sub-basins (e.g., Gunnison River)
GW groundwater	HUC12 A 12-digit Hydrologic Unit Code, referring to small watersheds
HCCD Historical Canadian Climate Data	
HCN Historical Climatology Network	

ICAR
Intermediate Complexity Atmospheric
Research model

ICS
intentionally created surplus

IDW
inverse distance weighting

IFS
integrated forecast system

IHC
initial hydrologic conditions

INSTAAR
Institute of Arctic and Alpine Research

IPCC
Intergovernmental Panel on Climate
Change

IPO
Interdecadal Pacific Oscillation

IRI
International Research Institute

iRON
Interactive Roaring Fork Observing Network

ISM
Index Sequential Method

JFM
January-February-March

JJA
June-July-August

K-NN
K-Nearest Neighbor

Landsat
Land Remote-Sensing Satellite (System)

LAST
Lane's Applied Stochastic Techniques

LERI
Landscape Evaporative Response Index

lidar
light detection and ranging

LOCA
Localized Constructed Analog

LSM
land surface model

M&I
municipal and industrial (water use
category)

MACA
Multivariate Adaptive Constructed Analog

maf
million acre-feet

MAM
March-April-May

MEFP
Meteorological Ensemble Forecast
Processor

METRIC
Mapping Evapotranspiration at high
Resolution with Internalized Calibration

MJO
Madden-Julian Oscillation

MMEFS
Met-Model Ensemble Forecast System

MOCOM
Multi-Objective Complex evolution

MODDRFS
MODIS Dust Radiative Forcing in Snow

MODIS Moderate Resolution Imaging Spectroradiometer	NCAR National Center for Atmospheric Research
MODIS LST (MYD11A2) Moderate Resolution Imaging Spectroradiometer Land Surface Temperature (MYD11A2)	NCCASC North Central Climate Adaptation Science Center
MODSCAG MODIS Snow Covered Area and Grain-size	NCECONET North Carolina Environment and Climate Observing Network
MPR Multiscale Parameter Regionalization	NCEI National Centers for Environmental Information
MRM Multiple Run Management	NCEP National Centers for Environmental Prediction
MT-CLIM (or MTCLIM) Mountain Climate simulator	nClimDiv new Climate Divisional (NOAA climate dataset)
MTOM Mid-Term Probabilistic Operations Model	NDBC National Data Buoy Center
NA-CORDEX North American Coordinated Regional Downscaling Experiment	NDVI Normalized Difference Vegetation Index
NAM North American Monsoon	NDWI Normalized Difference Water Index
NAO North Atlantic Oscillation	NEMO Nucleus for European Modelling of the Ocean (global ocean model)
NARCCAP North American Regional Climate Change Assessment Program	NevCan Nevada Climate-ecohydrological Assessment Network
NARR North American Regional Reanalysis	NGWOS Next-Generation Water Observing System
NASA National Aeronautics and Space Administration	NHMM Bayesian Nonhomogenous Hidden Markov Model
NASA JPL NASA Jet Propulsion Laboratory	

NICENET Nevada Integrated Climate and Evapotranspiration Network	NVDWR Nevada Department of Water Resources
NIDIS National Integrated Drought Information System	NWCC National Water and Climate Center
NLDAS North American Land Data Assimilation System	NWIS National Water Information System
NMME North American Multi-Model Ensemble	NWM National Water Model
NN R1 NCEP/NCAR Reanalysis	NWP numerical weather prediction
NOAA National Oceanic and Atmospheric Administration	NWS National Weather Service
NOAH Neural Optimization Applied Hydrology	NWSRFS National Weather Service River Forecast System
Noah-MP Noah-Multi-parameterization Model	NZI New Zealand Index
NOHRSC National Operational Hydrologic Remote Sensing Center	OCN Optimal Climate Normals
NPP Nonparametric paleohydrologic method	OHD Office of Hydrologic Development
NRCS Natural Resource Conservation Service	OK Mesonet Oklahoma Mesoscale Network
NSF National Science Foundation	ONI Oceanic Niño Index
NSIDC National Snow and Ice Data Center	OWAQ Office of Weather and Air Quality
NSMN National Soil Moisture Network	OWP Office of Water Prediction
	PC principal components
	PCA principal components analysis

PCR
principal components regression

PDO
Pacific Decadal Oscillation

PDSI
Palmer Drought Severity Index

PET
potential evapotranspiration

PGW
pseudo-global warming

PRISM
Parameter-elevation Relationships on
Independent Slopes Model

PSD
Physical Sciences Division

QBO
Quasi-Biennial Oscillation

QDO
Quasi-Decadal Oscillation

QM
quantile mapping

QPE
Quantitative Precipitation Estimate

QPF
Quantitative Precipitation Forecast

QTE
Quantitative Temperature Estimate

QTF
Quantitative Temperature Forecast

radar
radio detection and ranging

RAP
Rapid Refresh (weather model)

RAWS
Remote Automated Weather Station
Network

RCM
Regional Climate Model

RCP
Representative Concentration Pathway

RE
reduction-of-error

RFC
River Forecast Center

RFS
River Forecasting System

RH
relative humidity

RiverSMART
RiverWare Study Manager and Research
Tool

RMSE
root mean squared error

S/I
seasonal to interannual

S2S
subseasonal to seasonal

Sac-SMA
Sacramento Soil Moisture Accounting
Model

SAMS
Stochastic Analysis Modeling and
Simulation

SCA
snow-covered area

SCAN Soil Climate Analysis Network	SON September-October-November
SCE Shuffled Complex Evolution	SPoRT Short-term Prediction Research Transition
SCF seasonal climate forecast	SRES Special Report on Emissions Scenarios
SE standard error	SRP Salt River Project
SECURE Science and Engineering to Comprehensively Understand and Responsibly Enhance Water	SSEBOP Simplified Surface Energy Balance
SFWMD South Florida Water Management District	SSEBOP ET Simplified Surface Energy Balance Evapotranspiration
SM soil moisture	SSP Societally Significant Pathway
SMA Soil Moisture Accounting	SST sea surface temperatures
SMAP Soil Moisture Active Passive	SSW stratospheric sudden warming
SMHI Swedish Meteorological and Hydrological Institute	SubX Subseasonal Experiment
SMLR Screening Multiple Linear Regression	SUMMA Structure for Unifying Multiple Modeling Alternatives
SMOS Soil Moisture and Ocean Salinity	SVD singular value decomposition
SNODAS Snow Data Assimilation System	SW surface water
SNOTEL Snow Telemetry	SWANN Snow-Water Artificial Neural Network Modeling System
SOI Southern Oscillation Index	SWcasts Southwest Forecasts

SWE snow water equivalent	USCRN U.S. Climate Reference Network
SWOT Surface Water and Ocean Topography	USDA U.S. Department of Agriculture
SWS Statistical Water Supply	USGCRP U.S. Global Change Research Program
Tair air temperature	USGS U.S. Geological Survey
Tdew dew point temperature	USHCN United States Historical Climatology Network
TopoWx Topography Weather (climate dataset)	VIC Variable Infiltration Capacity (model)
TVA Tennessee Valley Authority	VIIRS Visible Infrared Imaging Radiometer Suite
UC Upper Colorado Region (Reclamation)	VPD vapor pressure deficit
UCAR University Corporation for Atmospheric Research	WBAN Weather Bureau Army Navy
UCBOR Upper Colorado Bureau of Reclamation	WCRP World Climate Research Program
UCRB Upper Colorado River Basin	WFO Weather Forecast Office
UCRC Upper Colorado River Commission	WPC Weather Prediction Center
UCRSFIG Upper Colorado Region State-Federal Interagency Group	WRCC Western Regional Climate Center
USACE U.S. Army Corps of Engineers	WRF Weather Research and Forecasting
USBR U.S. Bureau of Reclamation	WRF-Hydro WRF coupled with additional models to represent hydrologic processes

WSF

water supply forecast

WSWC

Western States Water Council

WUCA

Water Utility Climate Alliance

WWA

Western Water Assessment

WWCRA

West-Wide Climate Risk Assessments

WWMPP

Wyoming Weather Modification Pilot
Project

