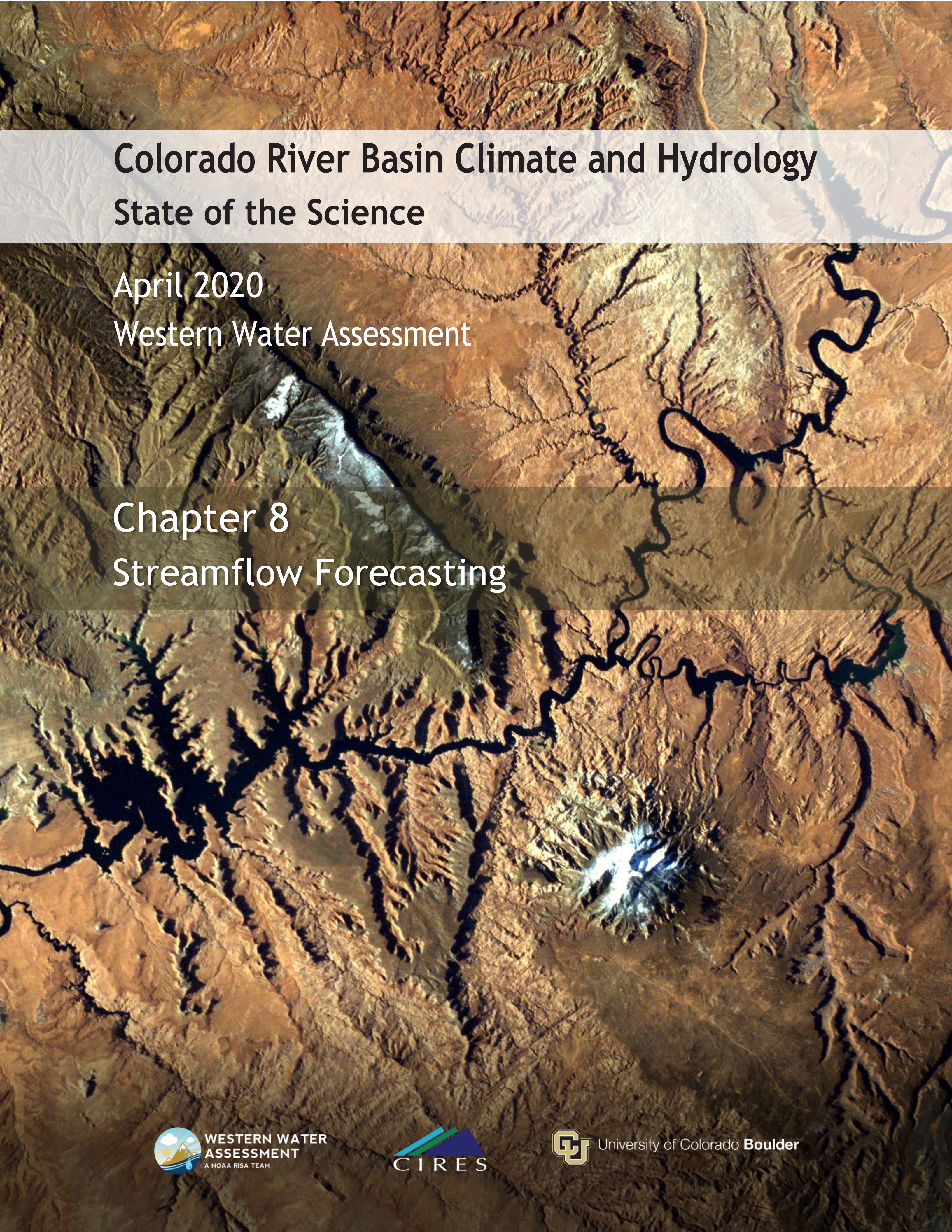

Colorado River Basin Climate and Hydrology

State of the Science

April 2020

Western Water Assessment

Chapter 8

Streamflow Forecasting

WESTERN WATER ASSESSMENT
A NOAA RISA TEAM
CIRES
University of Colorado Boulder

Colorado River Basin Climate and Hydrology
State of the Science

April 2020

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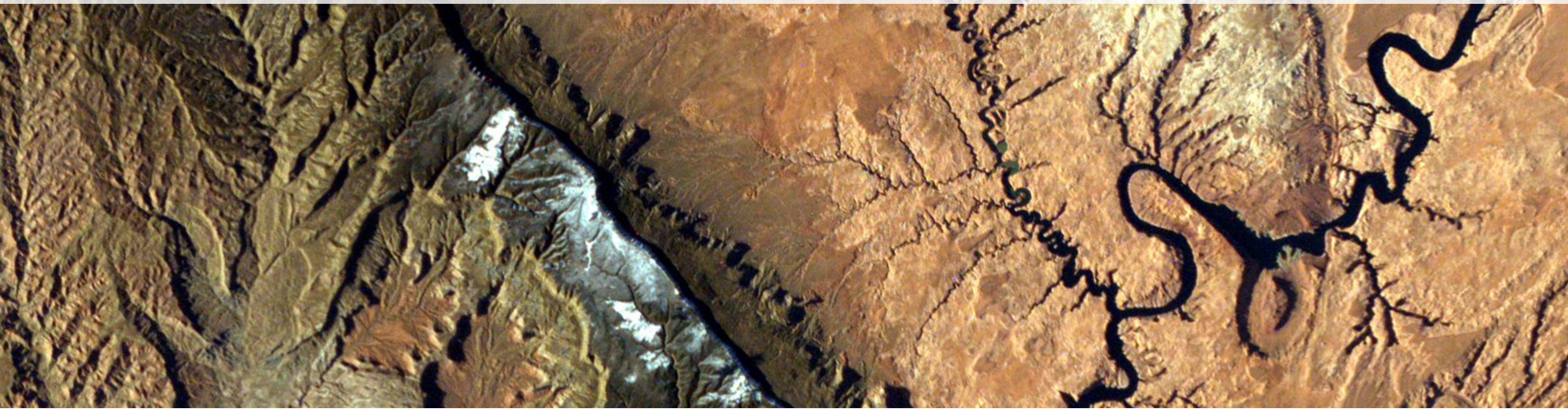
Volume III

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 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 gage 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.

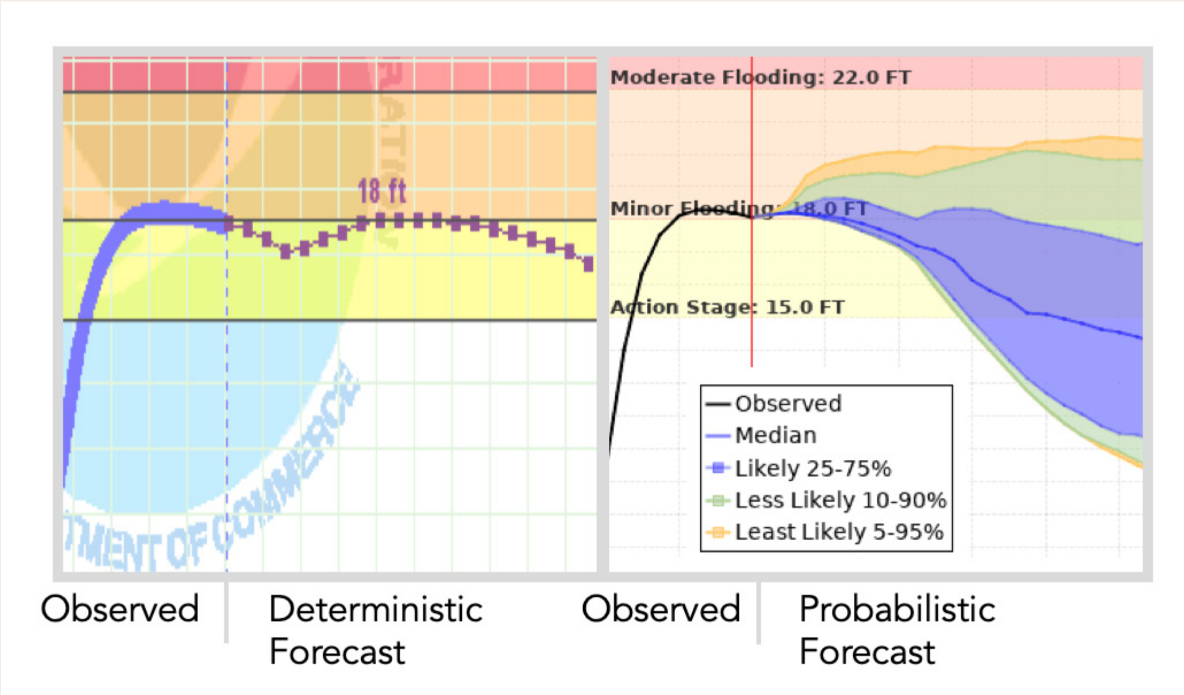


Figure 8.1

Deterministic single-value forecast (left) and probabilistic ensemble forecast (right) for the same stream gage (Little Wabash River, IL) and same 5-day period (March 12th–17th, 2020). The probabilistic forecast is based on an ensemble of streamflow forecasts that use different weather-forecast inputs. (Source: left: NOAA NWS AHPS; right: NOAA NWS OHRFC)

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.

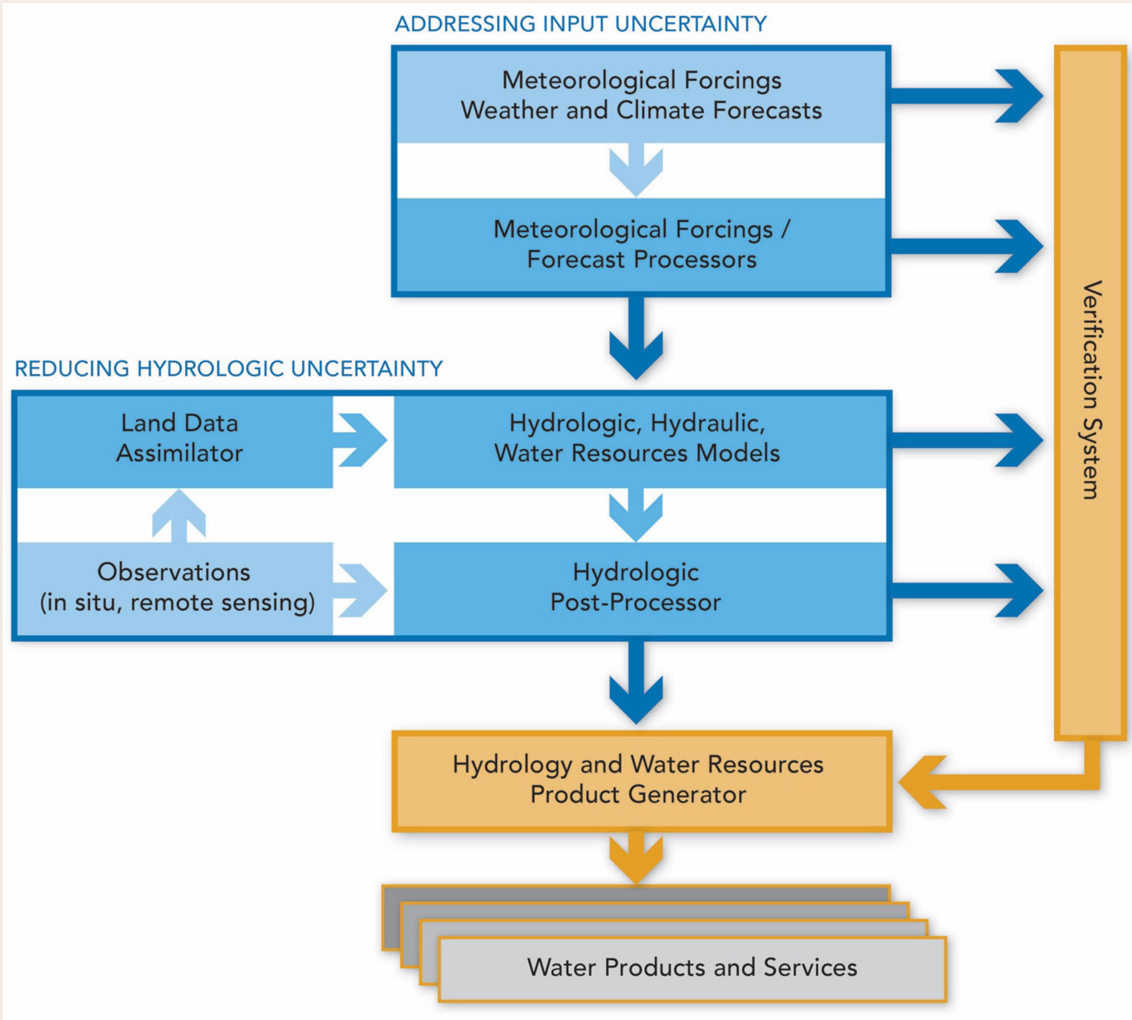


Figure 8.2

Schematic of a model-based streamflow forecasting system. (Source: adapted from NWS online materials: https://www.nws.noaa.gov/oh/hrl/hsmb/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.

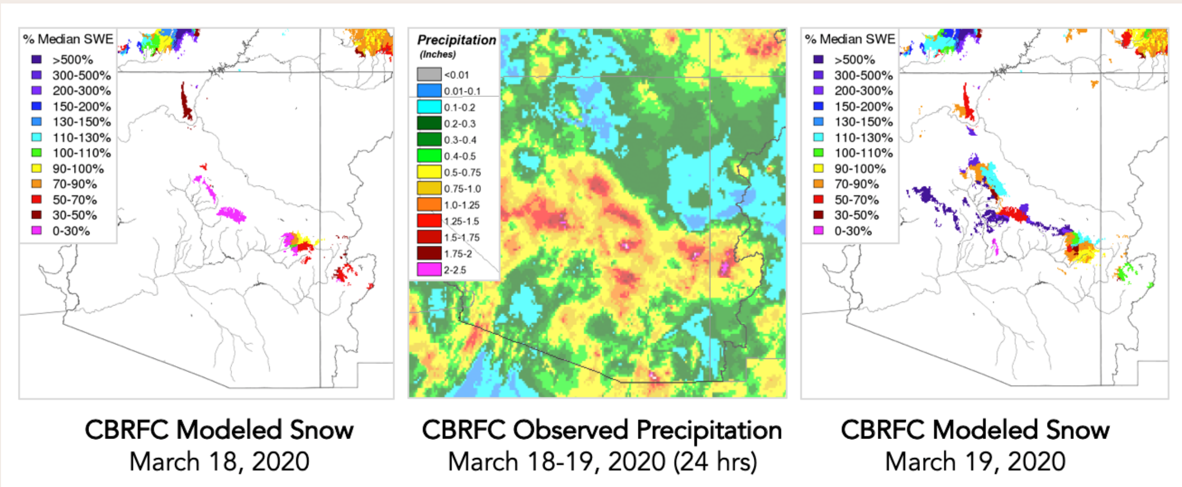


Figure 8.3

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.

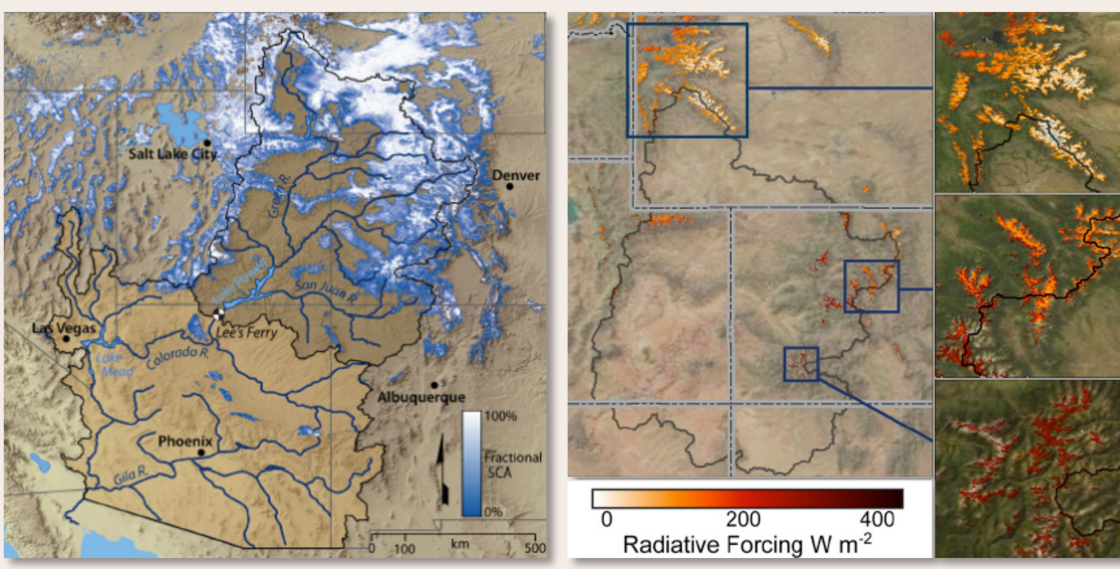


Figure 8.4

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.

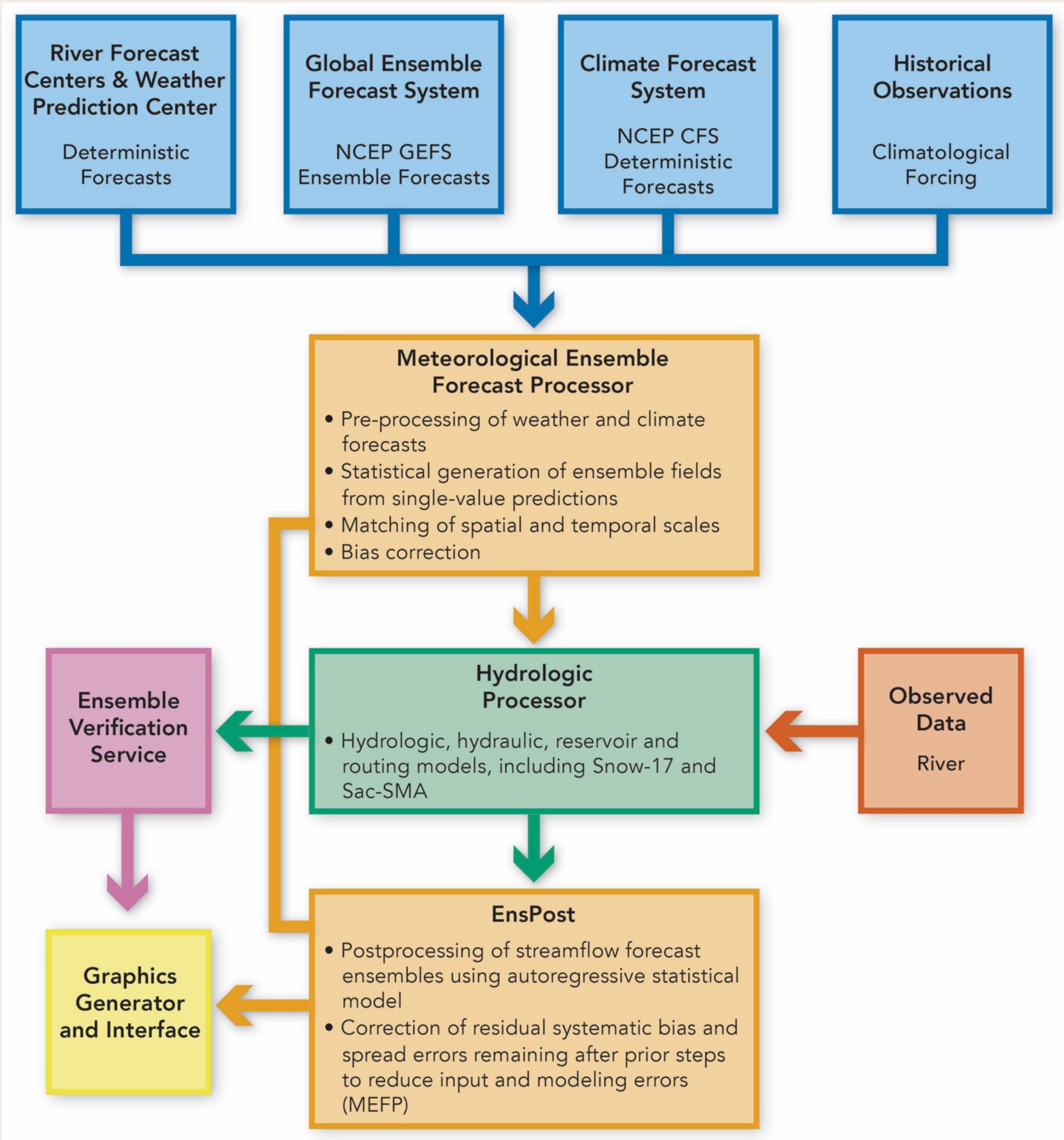


Figure 8.5

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—10^{th}, 50^{th} (most probable), and 90^{th}—although other quantiles such as the 30^{th} and 70^{th} 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 10^{th} and 90^{th} 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).

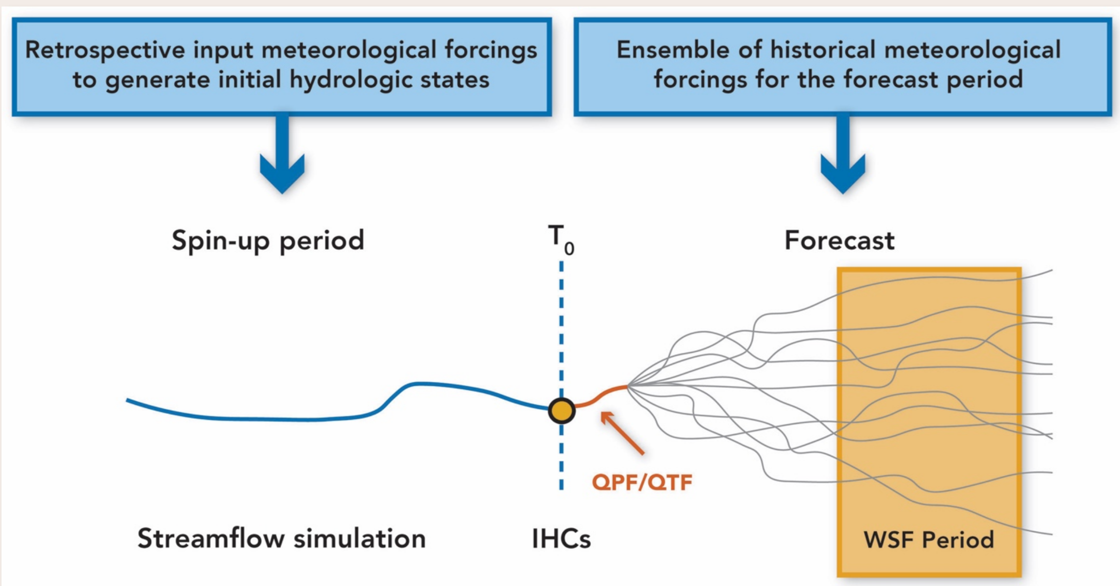


Figure 8.6

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.

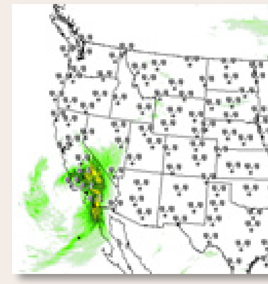
For mid-range forecasts at the CBRFC and other RFCs, the general ESP strategy of using a suite of historical sequences to represent the uncertainty in future climate over the next several months is slightly modified by inserting single-value precipitation and temperature forecasts for the first 5–10 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.).

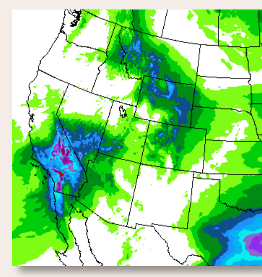
The CBRFC produces daily ESP forecasts of both unregulated and regulated streamflows (Chapter 5). Unregulated ESPs represent natural flow in the sense that measured upstream activities (e.g., reservoir operations or measured diversions) are estimated and their impacts on flow are reversed or backed out. 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 (10^{th}, 50^{th}, 90^{th}, 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.

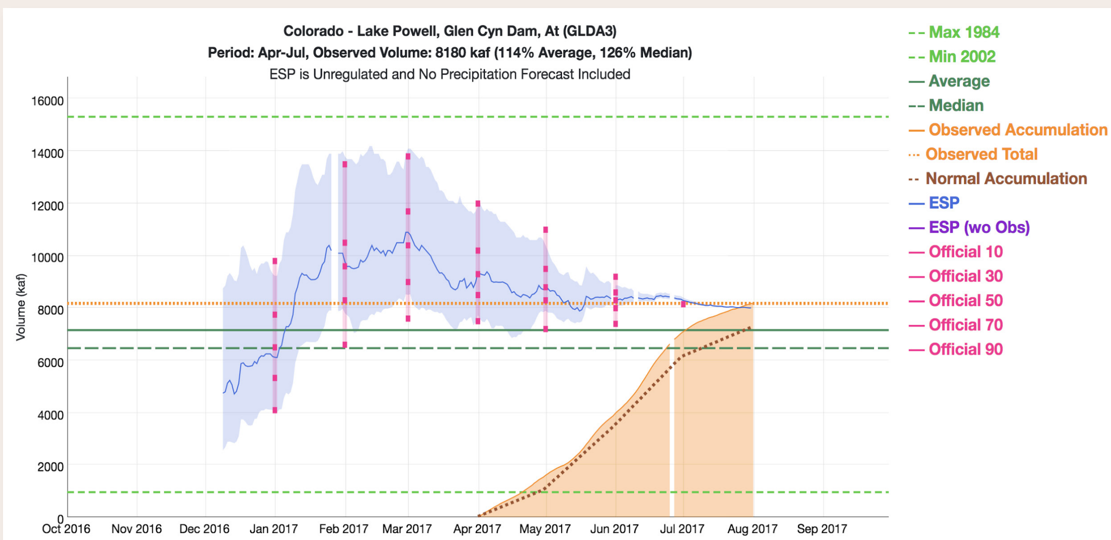


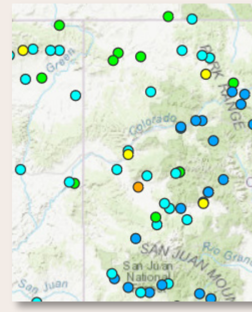
Figure 8.7

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.

Historical Water Supply Verification



Link: https://www.cbrfc.noaa.gov/arc/verif/verif.php

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.).

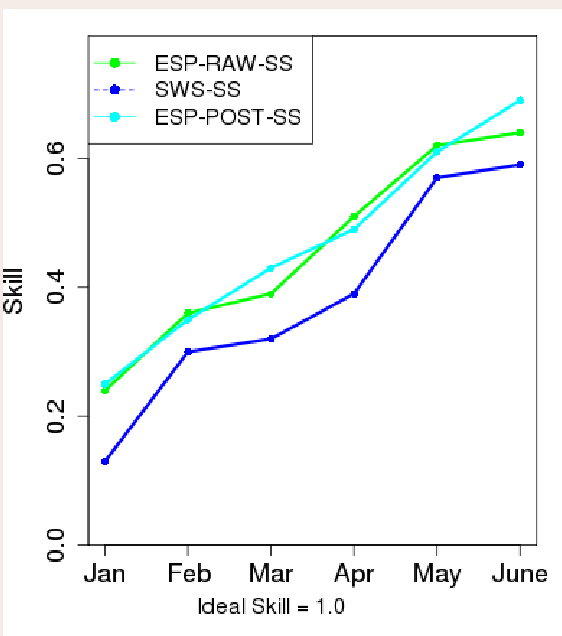


Figure 8.8

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.

	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	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	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	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	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	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	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	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	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	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
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
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
Sep												RFC	RFC	RFC	ESP Sep	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

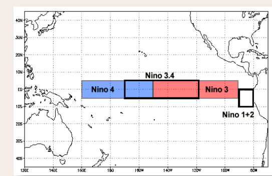
Ensemble trace weighting is one of the most common approaches for post-processing ESP forecasts to incorporate a climate signal. Hamlet and Lettenmaier (1999) used the current ENSO index to select ESP traces from ensemble members from years with similar ENSO conditions, while discarding other traces, 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.

Niño 3.4 Region Equatorial Pacific Sea Surface Temperatures



Link: https://www.ncdc.noaa.gov/teleconnections/enso/indicators/sst/

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).

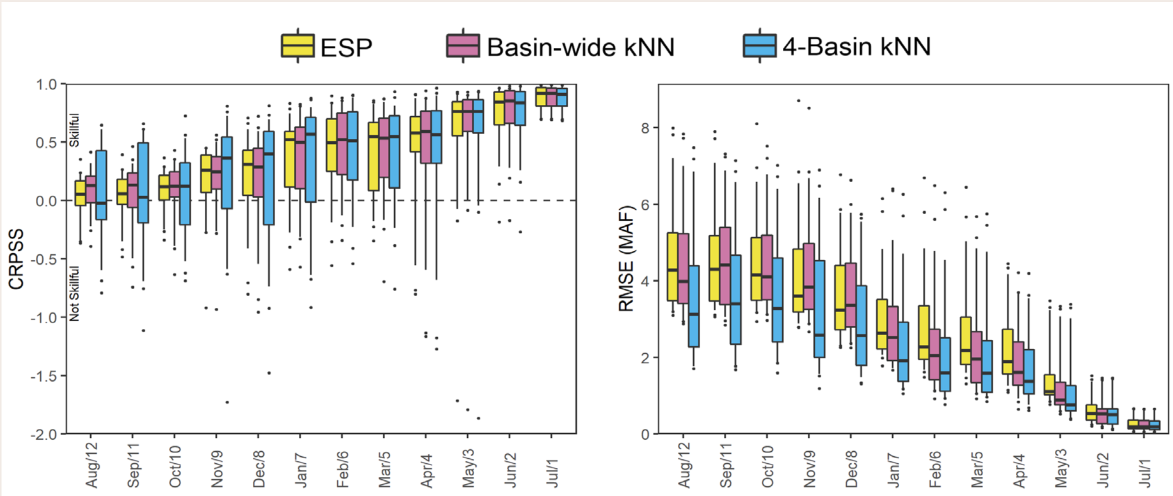


Figure 8.10

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.

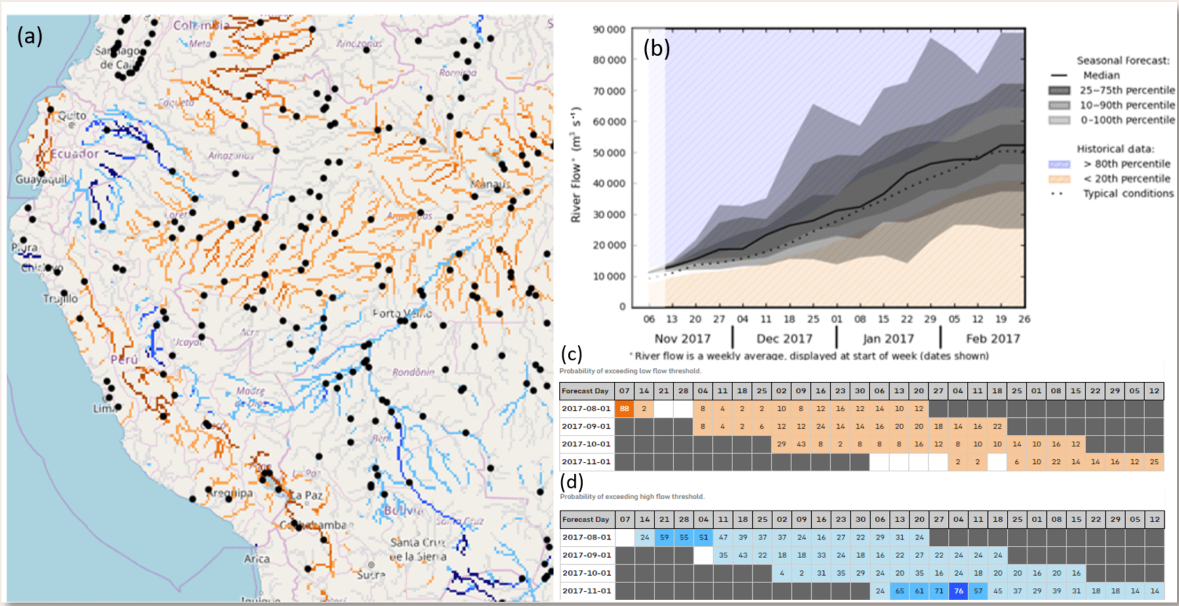


Figure 8.11

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 gage 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).

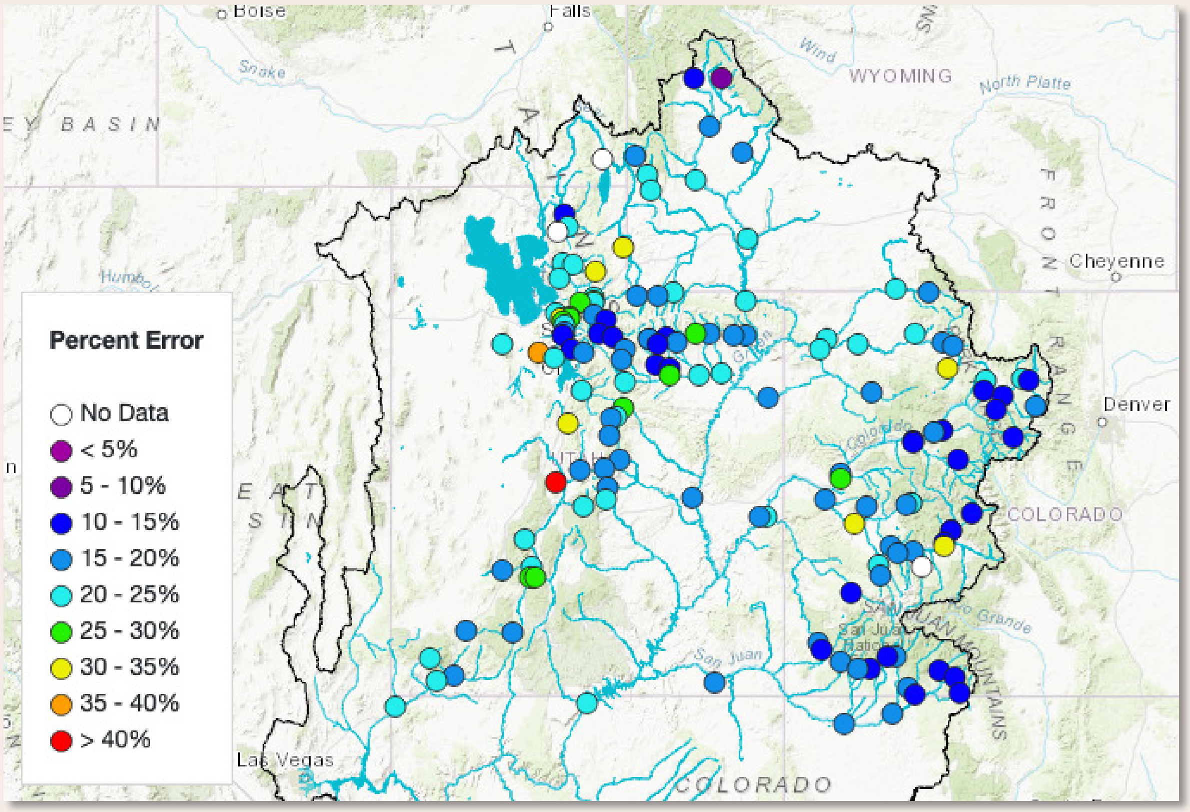


Figure 8.12

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 un-initialized 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.

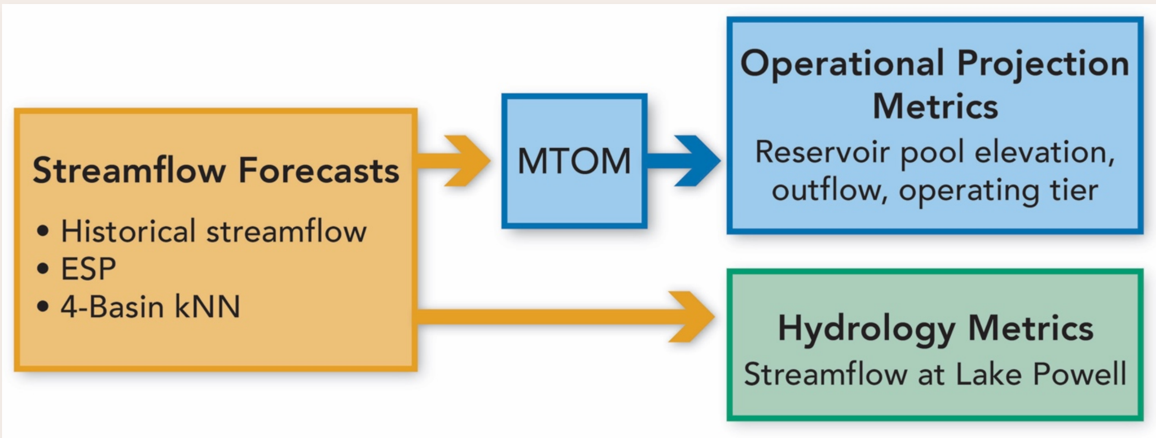


Figure 8.13

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.

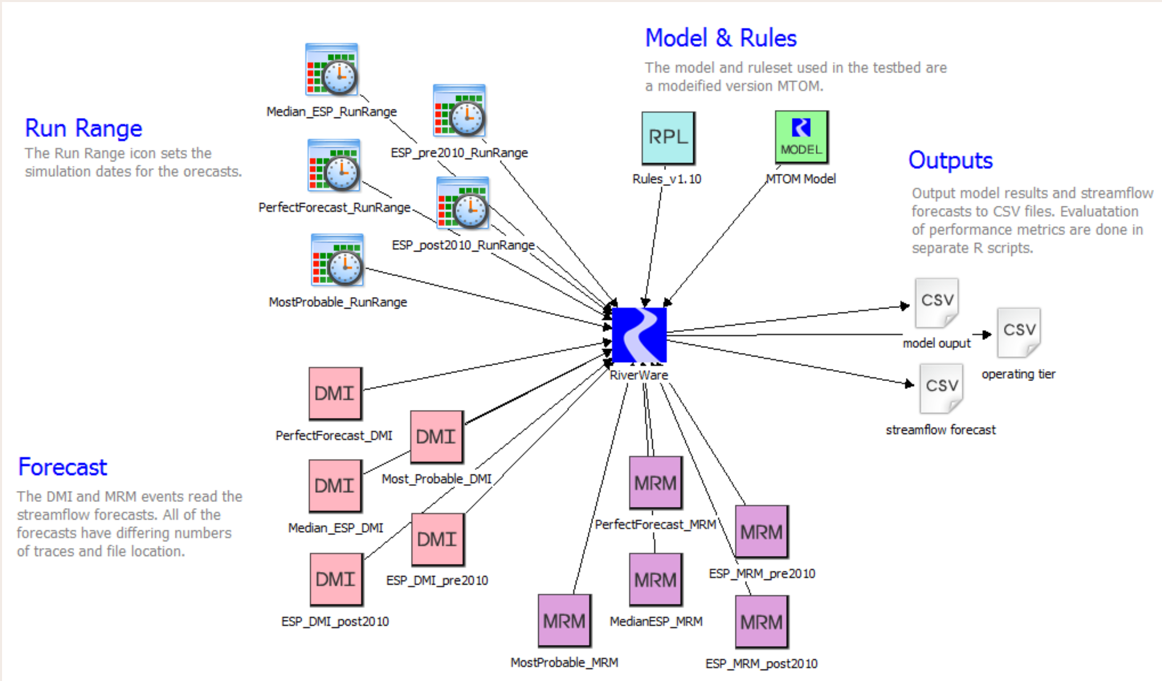


Figure 8.14

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](https://www.usbr.gov/lc/region/g4000/riverops/crss-5year-projections.html) 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 WorldWideHype 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.

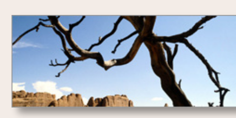
There is currently no shortage of techniques for incorporating climate information into mid-range hydrologic predictions (e.g., pre- and post-weighting methods), but the value of doing so is dependent on the skill of the input climate information. In locations where sub-seasonal and seasonal predictability 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](https://www.testbeds.noaa.gov/) 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.

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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 apportions 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.

R^2
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

CCSM4
Community Climate System Model, version 4 (global climate model)

CDEC
California Data Exchange Center

CDF
cumulative distribution function

CESM
Community Earth System Model (global climate model)

CFS
Climate/Coupled Forecast System

CFSv2
Coupled Forecast System version 2 (NOAA climate forecast model)

CHPS
Community Hydrologic Prediction System

CIMIS
California Irrigation Management Information System

CIR
crop irrigation requirement

CIRES
Cooperative Institute for Research in Environmental Sciences

CLIMAS
Climate Assessment for the Southwest

CLM
Community Land Model

CM2.1
Coupled Physical Model, version 2.1 (global climate model)

CMIP
Coupled Model Intercomparison Project (coordinated archive of global climate model output)

CNRFC
California-Nevada River Forecast Center

CoAgMET
Colorado Agricultural Meteorological Network

CoCoRaHS
Community Collaborative Rain, Hail and Snow Network

CODOS
Colorado Dust-on-Snow

CONUS
contiguous United States (the lower 48 states)

COOP
Cooperative Observer Program

CP
Central Pacific

CPC
Climate Prediction Center

CRB
Colorado River Basin

CRBPP
Colorado River Basin Pilot Project

CRPSS
Continuous Ranked Probability Skill Score

CRSM
Colorado River Simulation Model

CRSP
Colorado River Storage Project

CRSS
Colorado River Simulation System

CRWAS
Colorado River Water Availability Study
CSAS

CRWAS
Center for Snow and Avalanche Studies

CTSM
Community Terrestrial Systems Model

CU
consumptive use

CUL
consumptive uses and losses

CV
coefficient of variation

CVP/SWP
Central Valley Project/State Water Project

CWCB
Colorado Water Conservation Board

CWEST
Center for Water, Earth Science and Technology

DA
data assimilation

Daymet v.3
daily gridded surface meteorological data

DCP
Drought Contingency Plan

DEM
digital elevation model

DEOS
Delaware Environmental Observing System

DHSVM
Distributed Hydrology Soil Vegetation Model

DJF
December-January-February

DMDU
Decision Making Under Deep Uncertainty

DMI
Data Management Interface

DOD
Department of Defense

DOE
Department of Energy

DOW
Doppler [radar] on Wheels

DRI
Desert Research Institute

DTR
diurnal temperature range

EC
eddy-covariance method

EC
Environment Canada

ECCA
ensemble canonical correlation analysis

ECMWF
European Centre for Medium-Range Weather Forecasts

EDDI
Evaporative Demand Drought Index

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

ET_0
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)

FORTRAN
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

GHCN
Global Historical Climatology Network

GHCN-D
Global Historical Climate Network-Daily

GHG
greenhouse gas

GIS
geographic information system

GLOFAS
Global Flood Awareness System

GLOFFIS
Global Flood Forecast Information System

GOES
Geostationary Operational Environmental Satellite

GRACE
Gravity Recovery and Climate Experiment

GRIB
gridded binary or general regularly-distributed information in binary form

gridMET
Gridded Surface Meteorological dataset

GSSHA
Gridded Surface/Subsurface Hydrologic Analysis

GW
groundwater

HCCD
Historical Canadian Climate Data

HCN
Historical Climatology Network

HDA
hydrologic data assimilation

HDSC
Hydrometeorological Design Studies Center

HEFS
Hydrologic Ensemble Forecast Service

HESP
Hierarchical Ensemble Streamflow Prediction

HL-RDHM
Hydrologic Laboratory-Research Distributed Hydrologic Model

HMT
Hydromet Testbed

HP
hydrological processor

HRRR
High Resolution Rapid Refresh (weather model)

HSS
Heidke Skill Score

HTESSEL
Land-surface Hydrology Tiled ECMWF Scheme for Surface Exchanges over Land

HUC
Hydrologic Unit Code

HUC4
A 4-digit Hydrologic Unit Code, referring to large sub-basins (e.g., Gunnison River)

HUC12
A 12-digit Hydrologic Unit Code, referring to small watersheds

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

MODIS LST (MYD11A2)
Moderate Resolution Imaging Spectroradiometer Land Surface Temperature (MYD11A2)

MODSCAG
MODIS Snow Covered Area and Grain-size

MPR
Multiscale Parameter Regionalization

MRM
Multiple Run Management

MT-CLIM (or MTCLIM)
Mountain Climate simulator

MTOM
Mid-Term Probabilistic Operations Model

NA-CORDEX
North American Coordinated Regional Downscaling Experiment

NAM
North American Monsoon

NAO
North Atlantic Oscillation

NARCCAP
North American Regional Climate Change Assessment Program

NARR
North American Regional Reanalysis

NASA
National Aeronautics and Space Administration

NASA JPL
NASA Jet Propulsion Laboratory

NCAR
National Center for Atmospheric Research

NCCASC
North Central Climate Adaptation Science Center

NCECONET
North Carolina Environment and Climate Observing Network

NCEI
National Centers for Environmental Information

NCEP
National Centers for Environmental Prediction

nClimDiv
new Climate Divisional (NOAA climate dataset)

NDBC
National Data Buoy Center

NDVI
Normalized Difference Vegetation Index

NDWI
Normalized Difference Water Index

NEMO
Nucleus for European Modelling of the Ocean (global ocean model)

NevCan
Nevada Climate-ecohydrological Assessment Network

NGWOS
Next-Generation Water Observing System

NHMM
Bayesian Nonhomogenous Hidden Markov Model

NICENET
Nevada Integrated Climate and Evapotranspiration Network

NIDIS
National Integrated Drought Information System

NLDAS
North American Land Data Assimilation System

NMME
North American Multi-Model Ensemble

NN R1
NCEP/NCAR Reanalysis

NOAA
National Oceanic and Atmospheric Administration

NOAH
Neural Optimization Applied Hydrology

Noah-MP
Noah-Multi-parameterization Model

NOHRSC
National Operational Hydrologic Remote Sensing Center

NPP
Nonparametric paleohydrologic method

NRCS
Natural Resource Conservation Service

NSF
National Science Foundation

NSIDC
National Snow and Ice Data Center

NSMN
National Soil Moisture Network

NVDWR
Nevada Department of Water Resources

NWCC
National Water and Climate Center

NWIS
National Water Information System

NWM
National Water Model

NWP
numerical weather prediction

NWS
National Weather Service

NWSRFS
National Weather Service River Forecast System

NZI
New Zealand Index

OCN
Optimal Climate Normals

OHD
Office of Hydrologic Development

OK Mesonet
Oklahoma Mesoscale Network

ONI
Oceanic Niño Index

OWAQ
Office of Weather and Air Quality

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

SCE
Shuffled Complex Evolution

SCF
seasonal climate forecast

SE
standard error

SECURE
Science and Engineering to Comprehensively Understand and Responsibly Enhance Water

SFWMD
South Florida Water Management District

SM
soil moisture

SMA
Soil Moisture Accounting

SMAP
Soil Moisture Active Passive

SMHI
Swedish Meteorological and Hydrological Institute

SMLR
Screening Multiple Linear Regression

SMOS
Soil Moisture and Ocean Salinity

SNODAS
Snow Data Assimilation System

SNOTEL
Snow Telemetry

SOI
Southern Oscillation Index

SON
September-October-November

SPoRT
Short-term Prediction Research Transition

SRES
Special Report on Emissions Scenarios

SRP
Salt River Project

SSEBOP
Simplified Surface Energy Balance

SSEBOP ET
Simplified Surface Energy Balance Evapotranspiration

SSP
Societally Significant Pathway

SST
sea surface temperatures

SSW
stratospheric sudden warming

SubX
Subseasonal Experiment

SUMMA
Structure for Unifying Multiple Modeling Alternatives

SVD
singular value decomposition

SW
surface water

SWANN
Snow-Water Artificial Neural Network Modeling System

SWcasts
Southwest Forecasts

SWE
snow water equivalent

SWOT
Surface Water and Ocean Topography

SWS
Statistical Water Supply

Tair
air temperature

Tdew
dew point temperature

TopoWx
Topography Weather (climate dataset)

TVA
Tennessee Valley Authority

UC
Upper Colorado Region (Reclamation)

UCAR
University Corporation for Atmospheric Research

UCBOR
Upper Colorado Bureau of Reclamation

UCRB
Upper Colorado River Basin

UCRC
Upper Colorado River Commission

UCRSFIG
Upper Colorado Region State-Federal Interagency Group

USACE
U.S. Army Corps of Engineers

USBR
U.S. Bureau of Reclamation

USCRN
U.S. Climate Reference Network

USDA
U.S. Department of Agriculture

USGCRP
U.S. Global Change Research Program

USGS
U.S. Geological Survey

USHCN
United States Historical Climatology Network

VIC
Variable Infiltration Capacity (model)

VIIRS
Visible Infrared Imaging Radiometer Suite

VPD
vapor pressure deficit

WBAN
Weather Bureau Army Navy

WCRP
World Climate Research Program

WFO
Weather Forecast Office

WPC
Weather Prediction Center

WRCC
Western Regional Climate Center

WRF
Weather Research and Forecasting

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

WESTERN WATER ASSESSMENT
A NOAA RISA TEAM

CIRES

University of Colorado **Boulder**