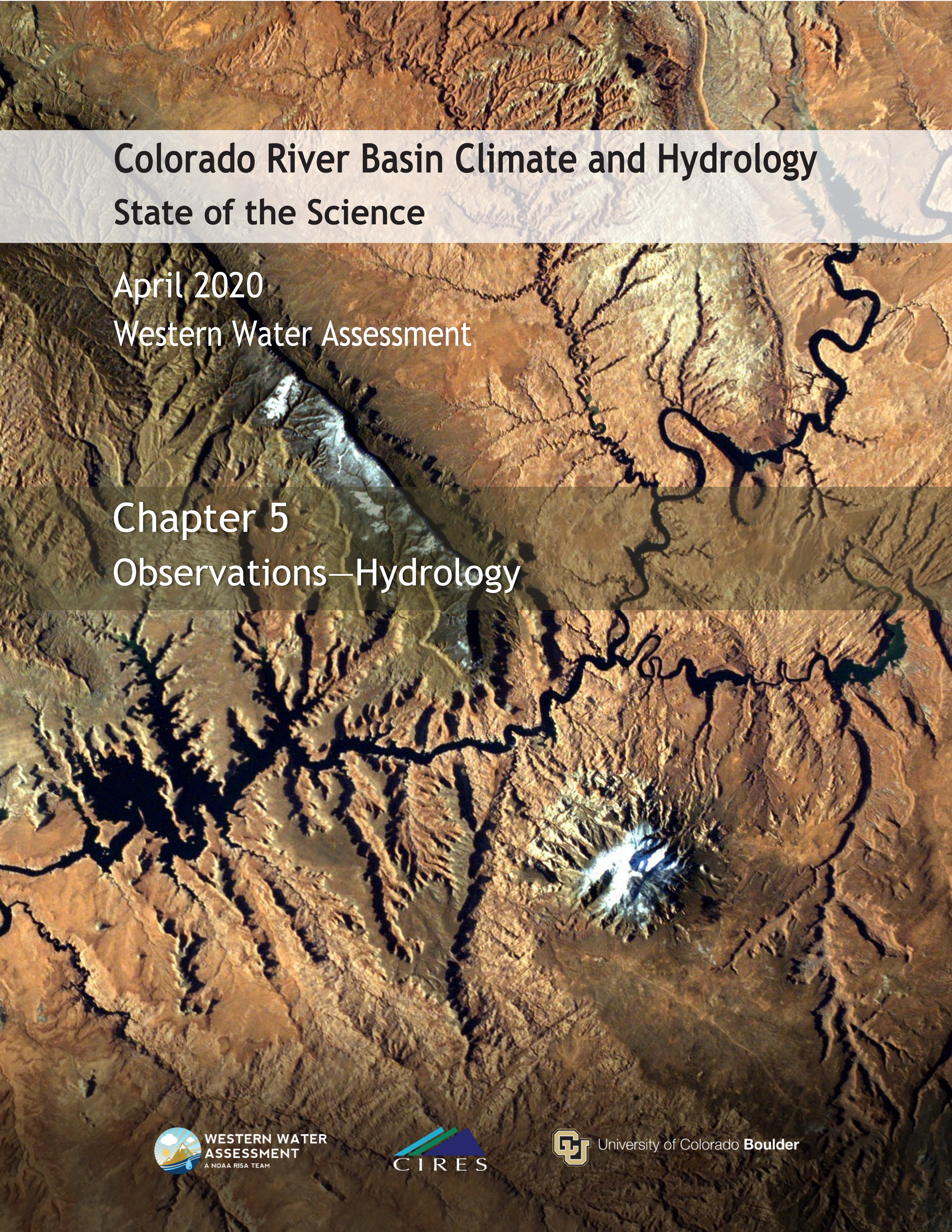

Colorado River Basin Climate and Hydrology

State of the Science

April 2020

Western Water Assessment

Chapter 5

Observations—Hydrology

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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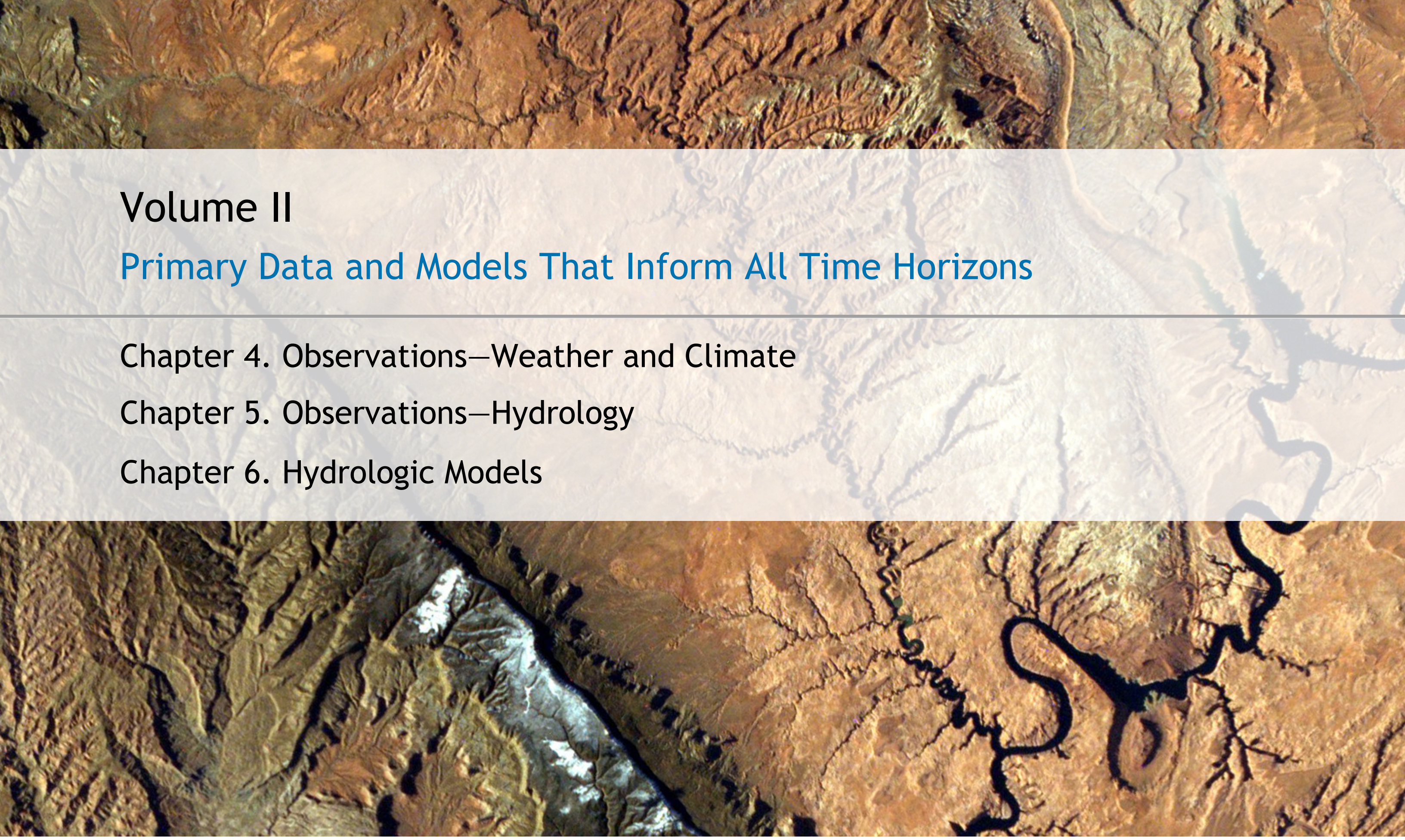

Volume II

Primary Data and Models That Inform All Time Horizons

Chapter 4. Observations—Weather and Climate

Chapter 5. Observations—Hydrology

Chapter 6. Hydrologic Models

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

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

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

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

Chapter 5

Observations—Hydrology

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Key points

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

5.1 Overview

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

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

5.2 Snowpack observations and monitoring

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

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

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

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

Table 5.1

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

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

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

In situ snowpack observations: SNOTEL and snow courses

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

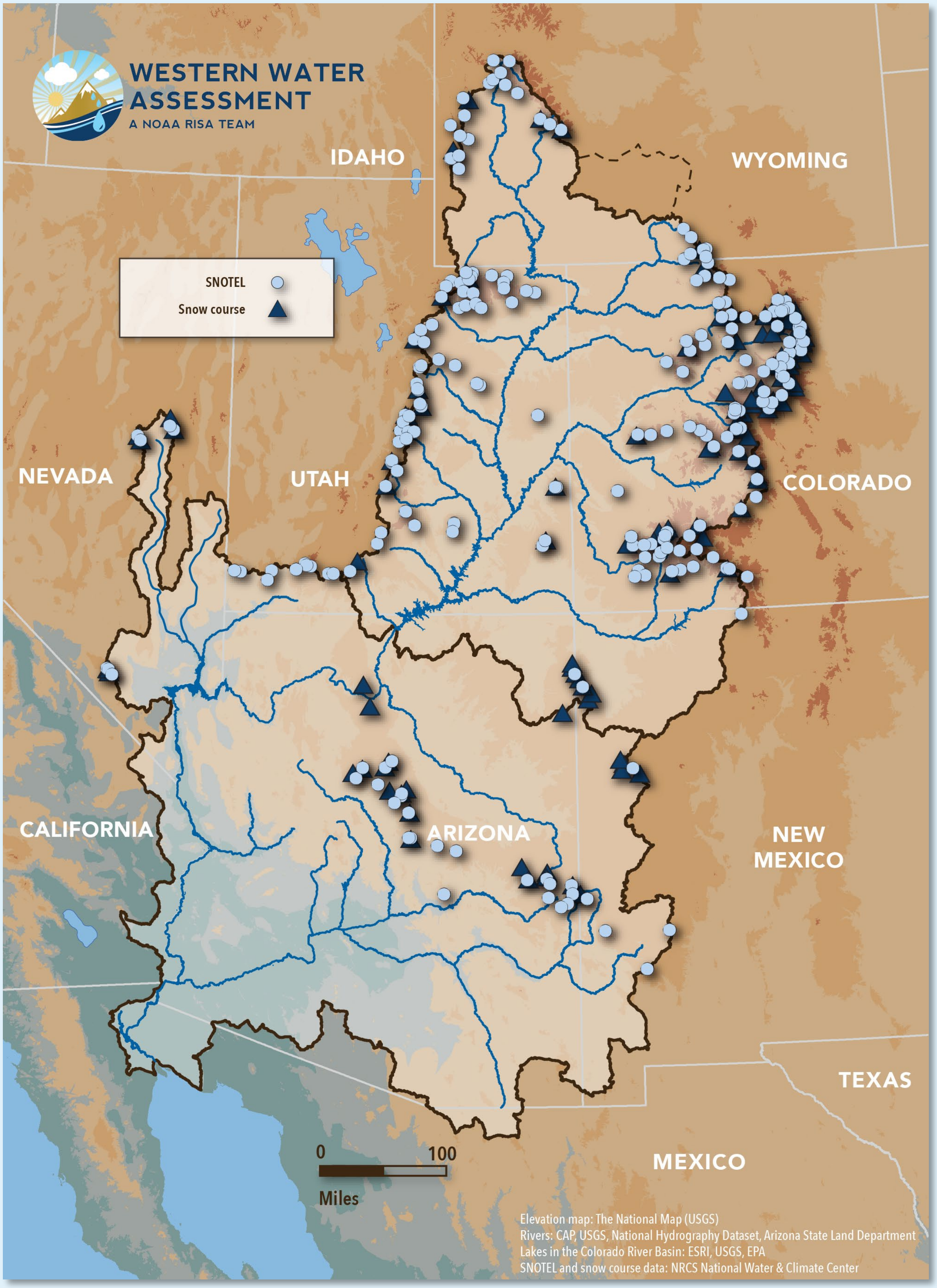
Figure 5.1
Soil Conservation Service (SCS) snow surveyors measuring a snow course in the 1940s. The SCS is now the Natural Resources Conservation Service (NRCS). (Source: Helms, Phillips, and Reich 2008)

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

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

NRCS Interactive Map

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

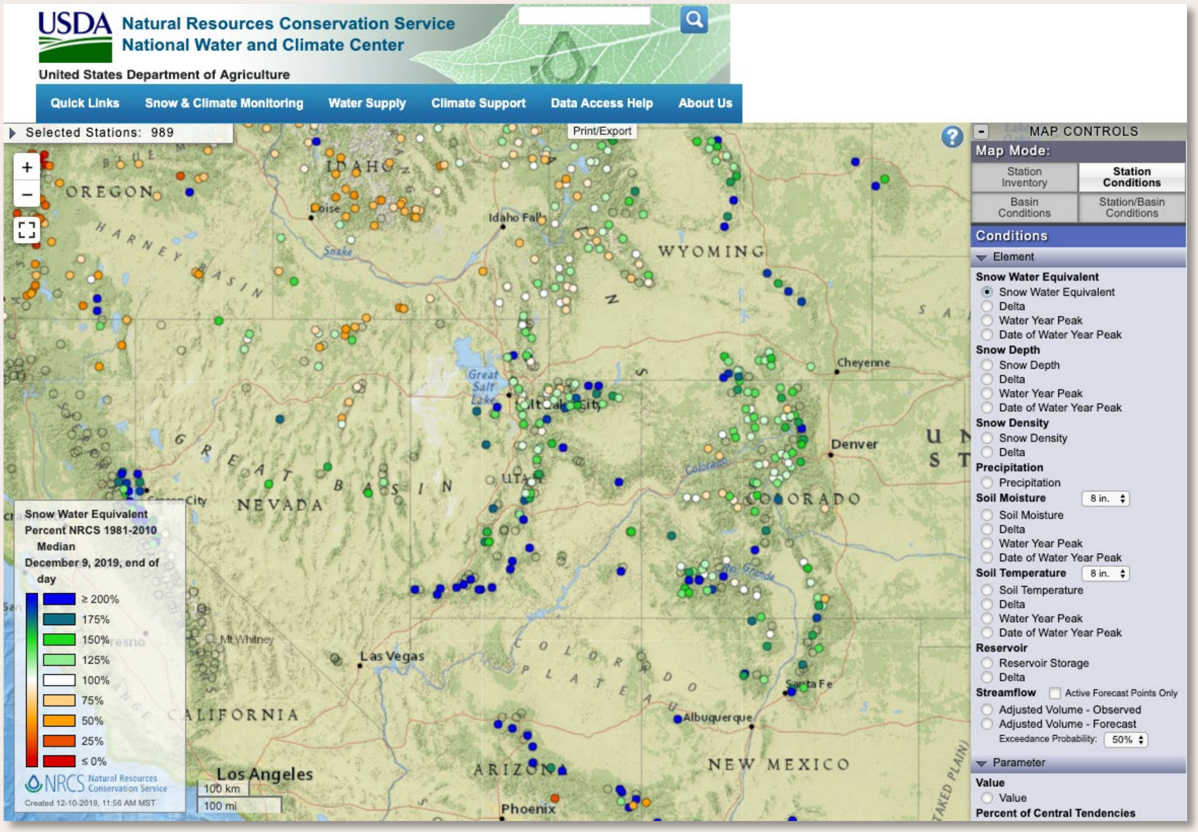


Elevation map: The National Map (USGS)
Rivers: CAP, USGS, National Hydrography Dataset, Arizona State Land Department
Lakes in the Colorado River Basin: ESRI, USGS, EPA
SNOTEL and snow course data: NRCS National Water & Climate Center

Figure 5.2

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

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



Selected Stations: 989

Station Conditions

Snow Water Equivalent ● Snow Water Equivalent

Figure 5.3

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

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

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

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

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

Despite some limitations, the point SWE observations from SNOTEL and snow courses continue to serve as the basis for skillful statistical forecasts of seasonal streamflows for the Colorado River Basin. However, the physical models also used to forecast runoff (e.g., CBRFC's primary forecast system) require additional modeling of the snowpack that directly addresses the issue of spatial representativeness, as well as additional input data, as detailed below. The more spatially explicit depiction of snowpack that results can also add value for general snow monitoring.

Other in situ snow observations

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

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

CoCoRaHS Network

Link:
https://www.cocorahs.org

Remote sensing of snow

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

MODIS, MODSCAG and MODDRFS

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

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

Airborne Snow Observatory (ASO)

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

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

What is LiDar?

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

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

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

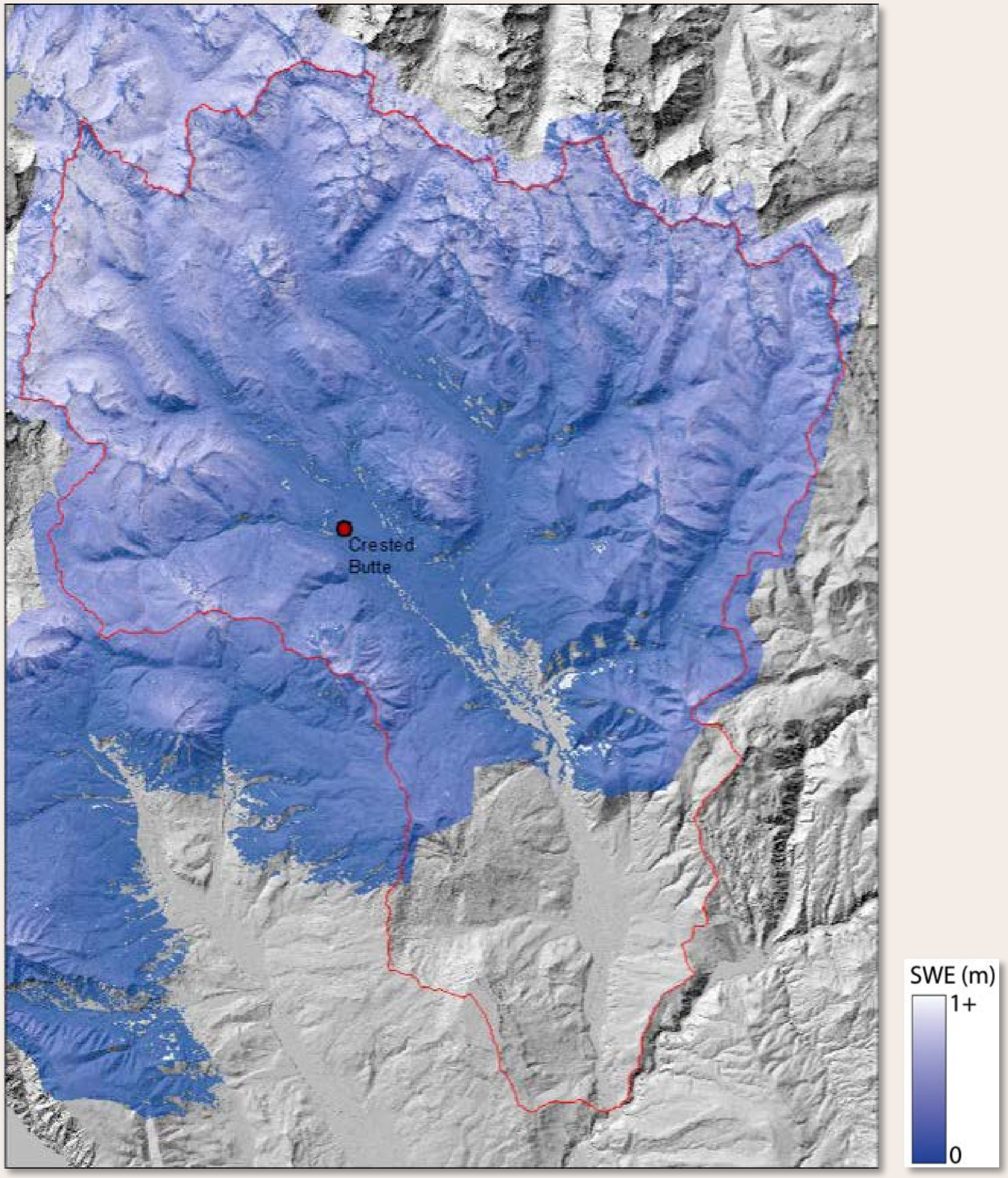


Figure 5.4

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

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

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

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

SPOTLIGHT

Winter orographic cloud seeding to enhance snowpack

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

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

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

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

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

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

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

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

Spatially distributed modeled snow products

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

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

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

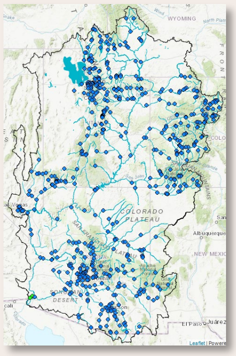
CBRFC modeled snowpack

For operational streamflow forecasting, the CBRFC pairs a snow model (SNOW-17) with a hydrology model (Sac-SMA; see Chapter 8). SNOW-17 is run in a spatially "lumped" or partially distributed framework, meaning that area averages are calculated for each modeling unit, with each unit typically representing an elevation zone, of which there are usually three in each watershed. The mean area precipitation for a modeling unit is calculated from the precipitation observations at one or more SNOTEL or COOP stations, using weightings determined by model calibration and the PRISM precipitation climatology (Bender et al. 2014). In the Upper Basin, 6-hourly precipitation data is used, while in the Lower Basin, hourly data is used. SNOW-17 then builds a simulated snowpack, using the temperatures observed at the SNOTEL sites and local freezing levels, to determine whether precipitation is falling as snow or rain, and whether the snowpack is accumulating or ablating. Historical precipitation observations are used to calibrate the snow model. The model effectively estimates a snow-water volume for each modeling unit, and thus for each watershed, sub-basin, and basin, which is then used to model the forecasted spring-summer streamflow volume (Bender et al. 2014). The model allows snow to persist at the highest elevations even after most or all SNOTEL sites have melted out, consistent with real-world behavior of the snowpack.

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

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

CBRFC Colorado Basin River Forecast Center



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

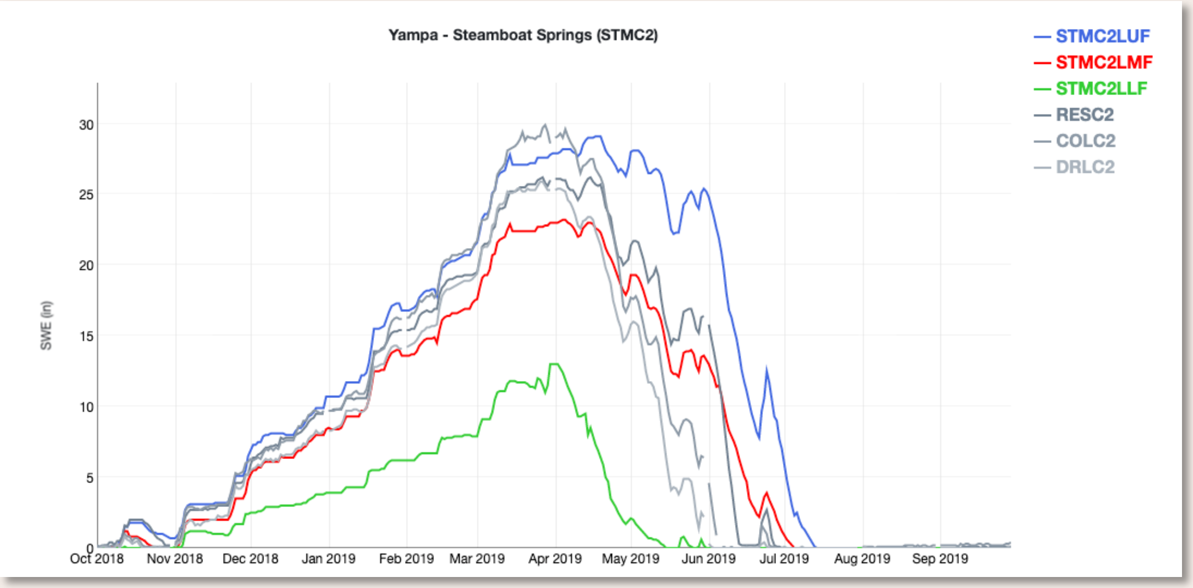


Figure 5.5

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

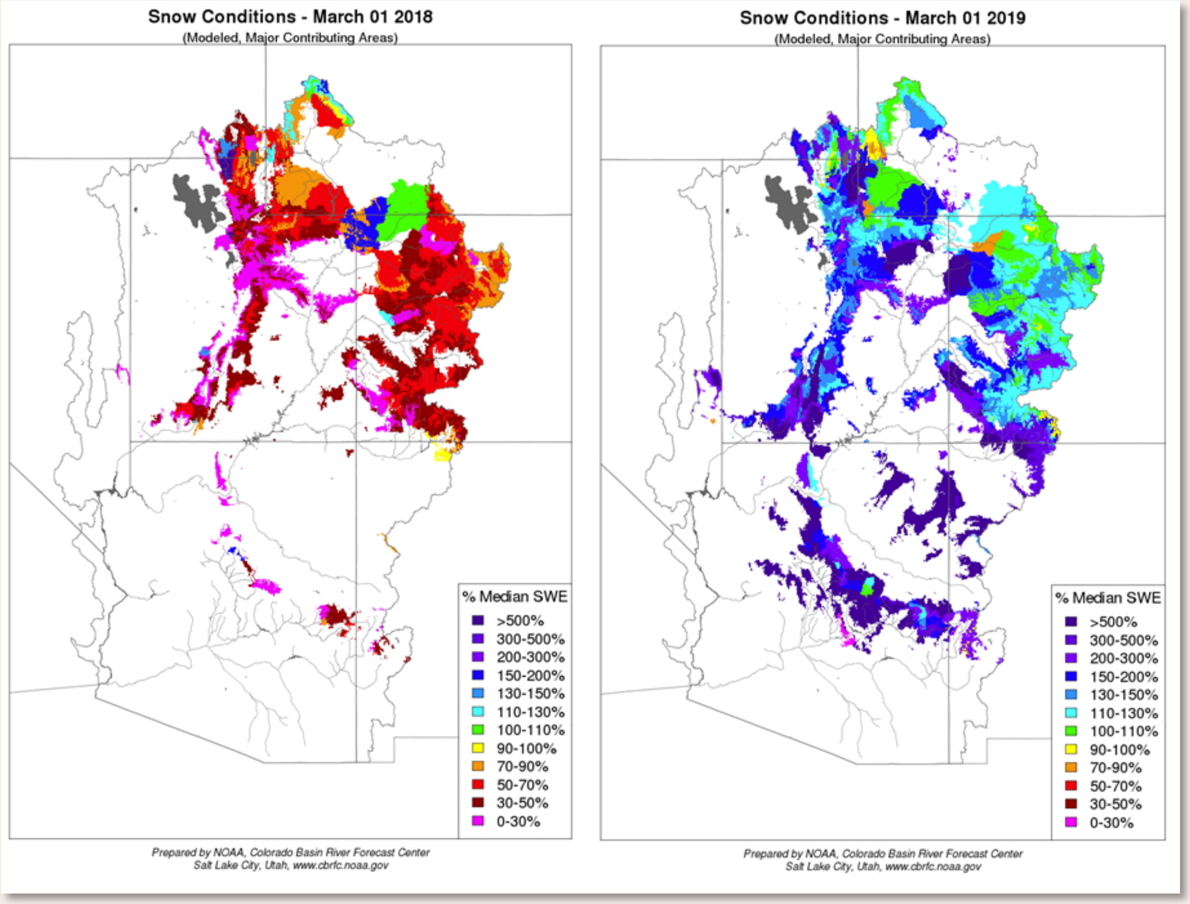


Figure 5.6

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

SNODAS (NOAA NOHRSC)

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

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

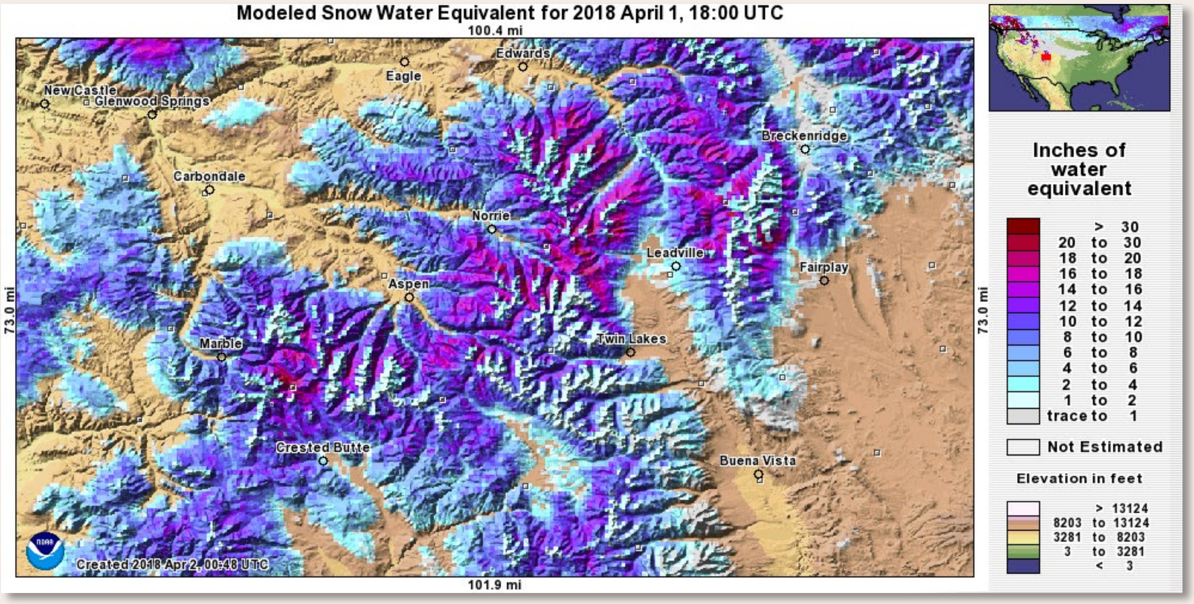


Figure 5.7

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

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

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

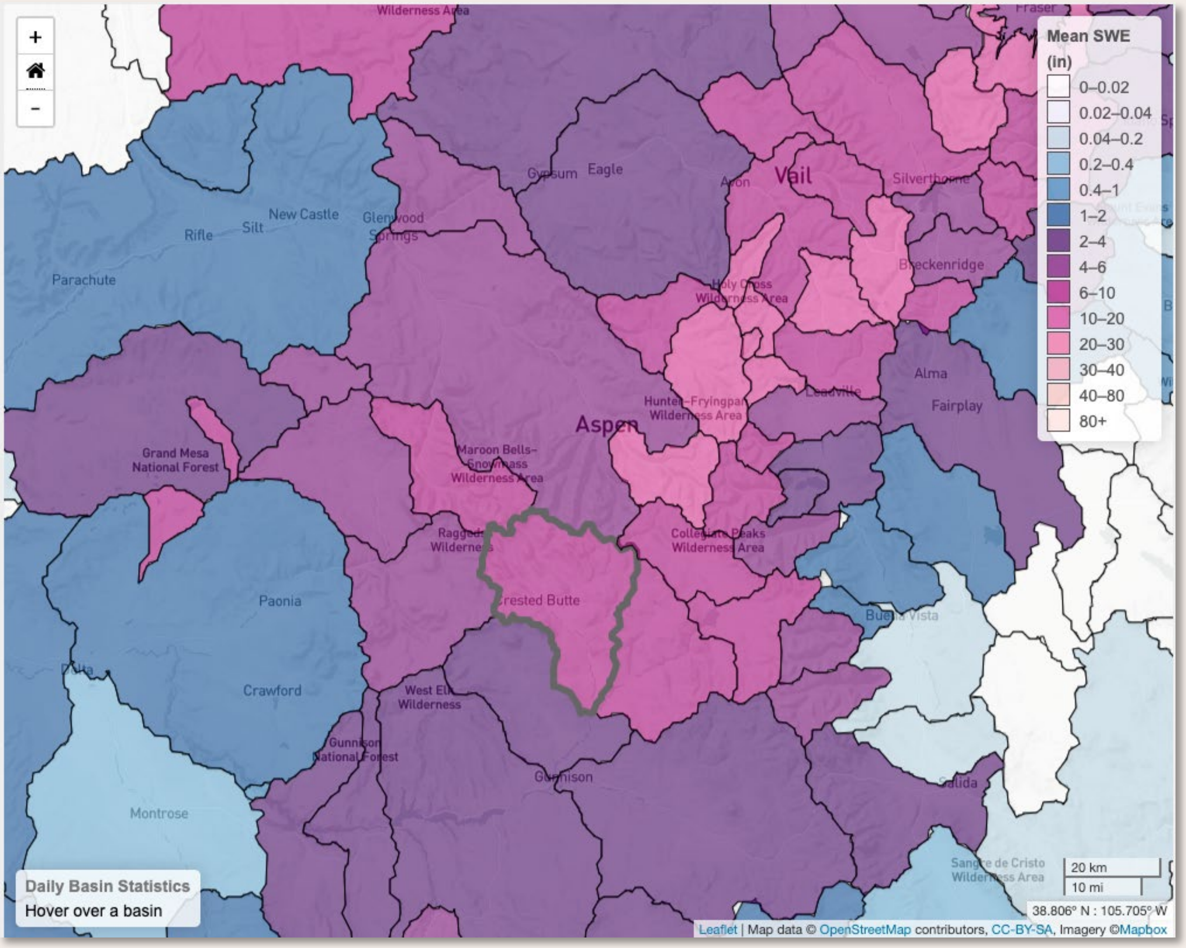


Figure 5.8

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

MODIS-based spatial estimates of SWE

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

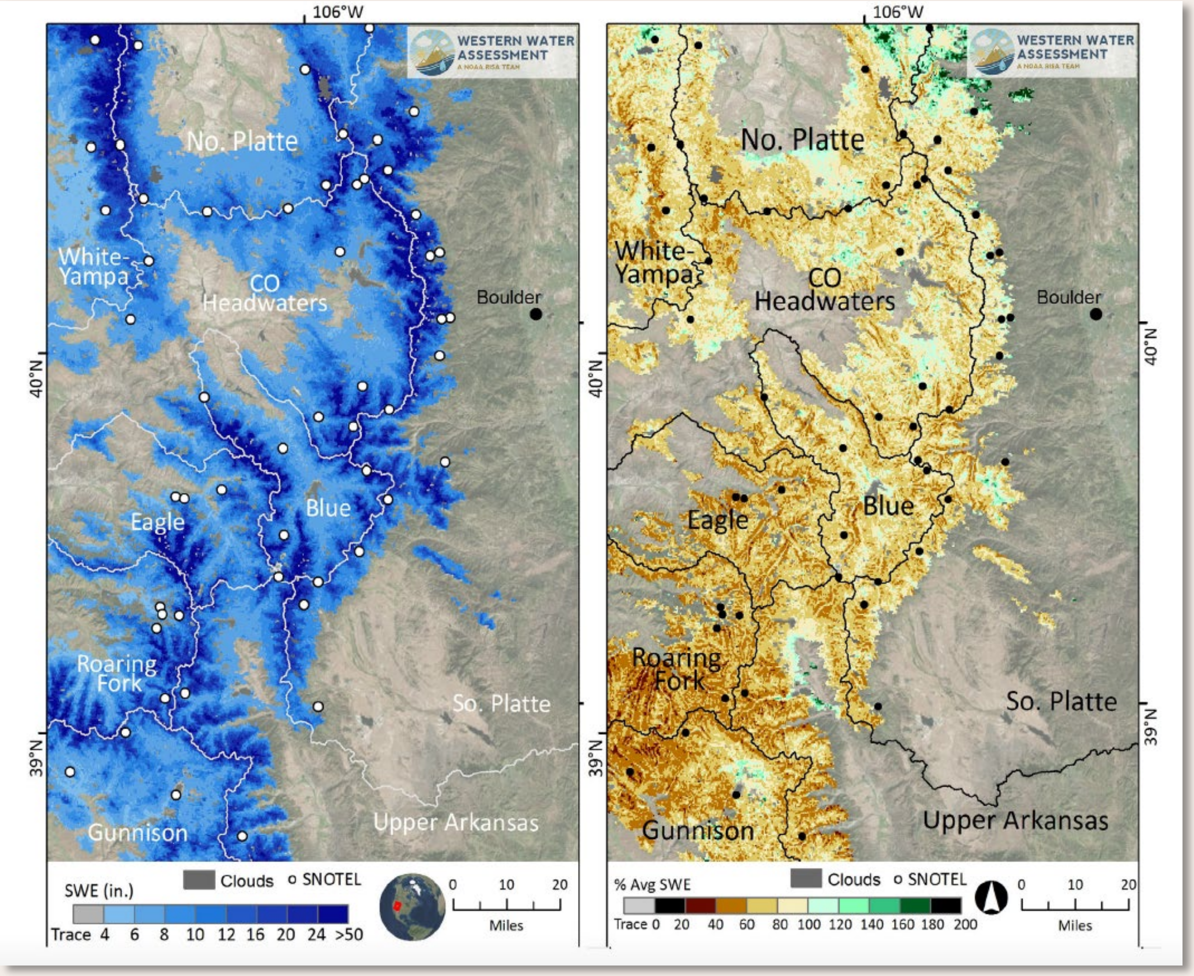


Figure 5.9

MODIS-based spatial estimates of SWE at 500-m resolution across the Colorado headwaters sub-region. The SWE amounts for April 3, 2018 are shown in the left panel, and the % of average SWE for April 3, 2018 (relative to the 2001-2012 average) over the snow-covered area is shown in the right panel. (Source: CU INSTAAR/CWEST)

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

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

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

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

SWANN: The Snow Water Artificial Neural Network

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

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

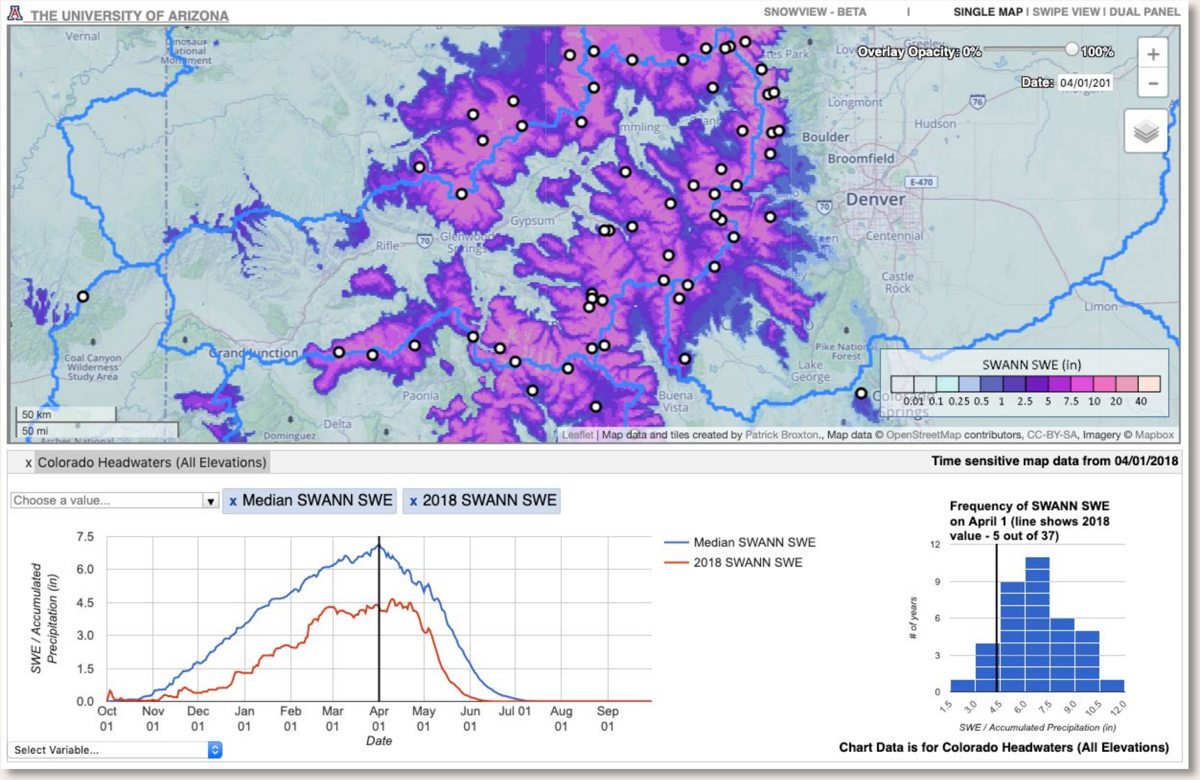


Figure 5.10

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

Challenges and opportunities in snow observations

As noted above, the SNOTEL snow-monitoring system serves its central purpose well, as indicated by the generally high skill of seasonal water supply forecasts that rely on SNOTEL data. However, the assumption of spatial representativeness underpinning these monitoring and forecasting systems is less robust in years with unusual conditions, e.g., an overall average snowpack with above average low-elevation snow. The larger forecast errors that occur in these cases can potentially be reduced by better real-time characterization of those aspects of the snowpack's spatial distribution that are not captured well by SNOTEL. In order to take full advantage of this enhanced spatial information, though, streamflow forecasting systems need to be able to efficiently take in these data—which is not the case for the current CBRFC or NRCS systems.

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

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

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

SPOTLIGHT

Dust-on-snow in the Colorado River Basin

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

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

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

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

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

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

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

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

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

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

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

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

5.3 Streamflow observations and monitoring

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

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

Gaged streamflows

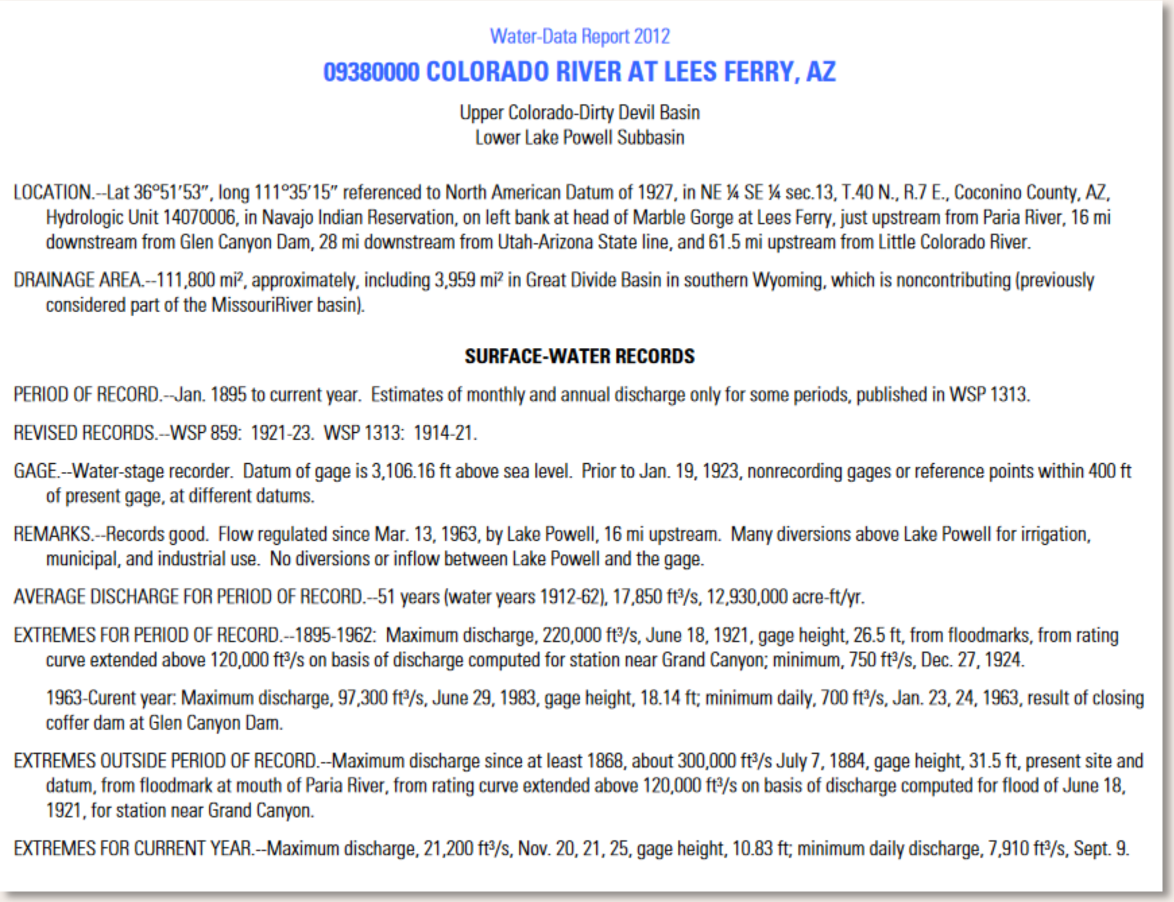
The USGS is the primary entity that operates and maintains stream gages. Within the Colorado River Basin, Reclamation, the basin states, and dozens of other entities also maintain, operate and fund stream gages through their participation in the Cooperative Water Program (Interstate Council on Water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

USGS National Water Information System

Link: https://waterdata.usgs.gov/nwis/

Streamflow gage uncertainty

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



Water-Data Report 2012

09380000 COLORADO RIVER AT LEES FERRY, AZ

Upper Colorado-Dirty Devil Basin
Lower Lake Powell Subbasin

LOCATION.--Lat 36°51′53″, long 111°35′15″ referenced to North American Datum of 1927, in NE ¼ SE ¼ sec.13, T.40 N., R.7 E., Coconino County, AZ, Hydrologic Unit 14070006, in Navajo Indian Reservation, on left bank at head of Marble Gorge at Lees Ferry, just upstream from Paria River, 16 mi downstream from Glen Canyon Dam, 28 mi downstream from Utah-Arizona State line, and 61.5 mi upstream from Little Colorado River.

DRAINAGE AREA.--111,800 mi^2, approximately, including 3,959 mi^2 in Great Divide Basin in southern Wyoming, which is noncontributing (previously considered part of the MissouriRiver basin).

SURFACE-WATER RECORDS

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

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

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

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

AVERAGE DISCHARGE FOR PERIOD OF RECORD.--51 years (water years 1912-62), 17,850 ft^3/s, 12,930,000 acre-ft/yr.

EXTREMES FOR PERIOD OF RECORD.--1895-1962: Maximum discharge, 220,000 ft^3/s, June 18, 1921, gage height, 26.5 ft, from floodmarks, from rating curve extended above 120,000 ft^3/s on basis of discharge computed for station near Grand Canyon; minimum, 750 ft^3/s, Dec. 27, 1924.

1963-Curent year: Maximum discharge, 97,300 ft^3/s, June 29, 1983, gage height, 18.14 ft; minimum daily, 700 ft^3/s, Jan. 23, 24, 1963, result of closing coffer dam at Glen Canyon Dam.

EXTREMES OUTSIDE PERIOD OF RECORD.--Maximum discharge since at least 1868, about 300,000 ft^3/s July 7, 1884, gage height, 31.5 ft, present site and datum, from floodmark at mouth of Paria River, from rating curve extended above 120,000 ft^3/s on basis of discharge computed for flood of June 18, 1921, for station near Grand Canyon.

EXTREMES FOR CURRENT YEAR.--Maximum discharge, 21,200 ft^3/s, Nov. 20, 21, 25, gage height, 10.83 ft; minimum daily discharge, 7,910 ft^3/s, Sept. 9.

Figure 5.11

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

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

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

Federal priority stream gages

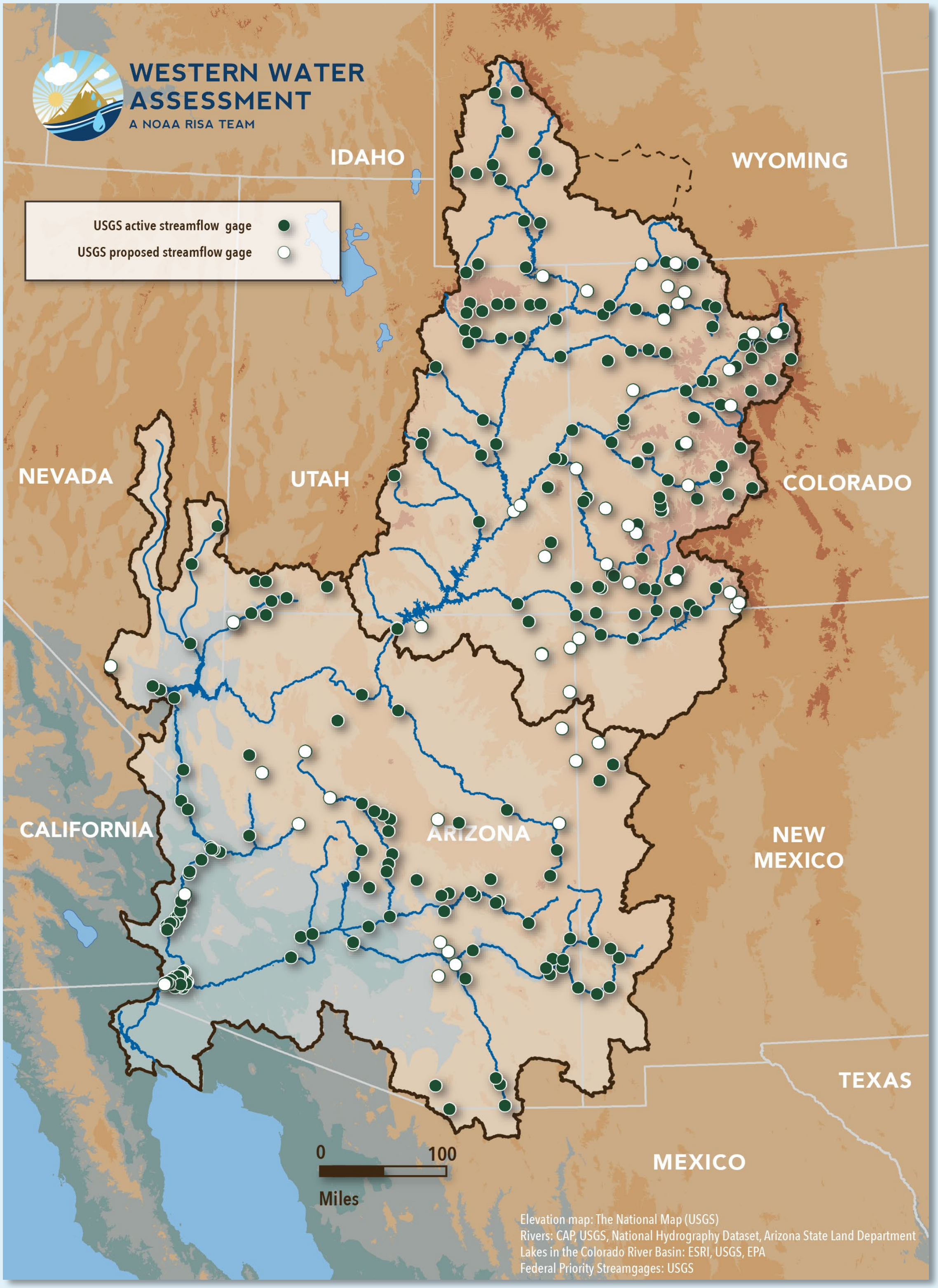
A subset of USGS streamflow gages are part of the "Federal Priority Streamgages" (FPS) network, a group of gages that are considered critical for federal support of forecasting, compact and border agreements, analysis of long-term trends, and other purposes (US Geological Survey 2018a). The FPS network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

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

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

USGS Federal Priority Stream Gage Network

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



Elevation map: The National Map (USGS)
Rivers: CAP, USGS, National Hydrography Dataset, Arizona State Land Department
Lakes in the Colorado River Basin: ESRI, USGS, EPA
Federal Priority Streamgages: USGS

Figure 5.12

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

> “The streamgaging network … has had to contend with unstable and discontinuous funding support. Gages have been inactivated when cooperators cut budgets, and these incremental losses have eroded the network. Many inactivated gages had long records that are valuable for trend analysis and forecasting. It is practically impossible to quantify the cost of losing an individual gage. Its value even for one goal—for example, flood or drought forecasting—is embedded in the operation and accuracy of the entire forecast system, the forecast delivery mechanisms, and the forecast response.”
>
> National Research Council (2004)

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

Streamflow data gaps in the Colorado River Basin

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

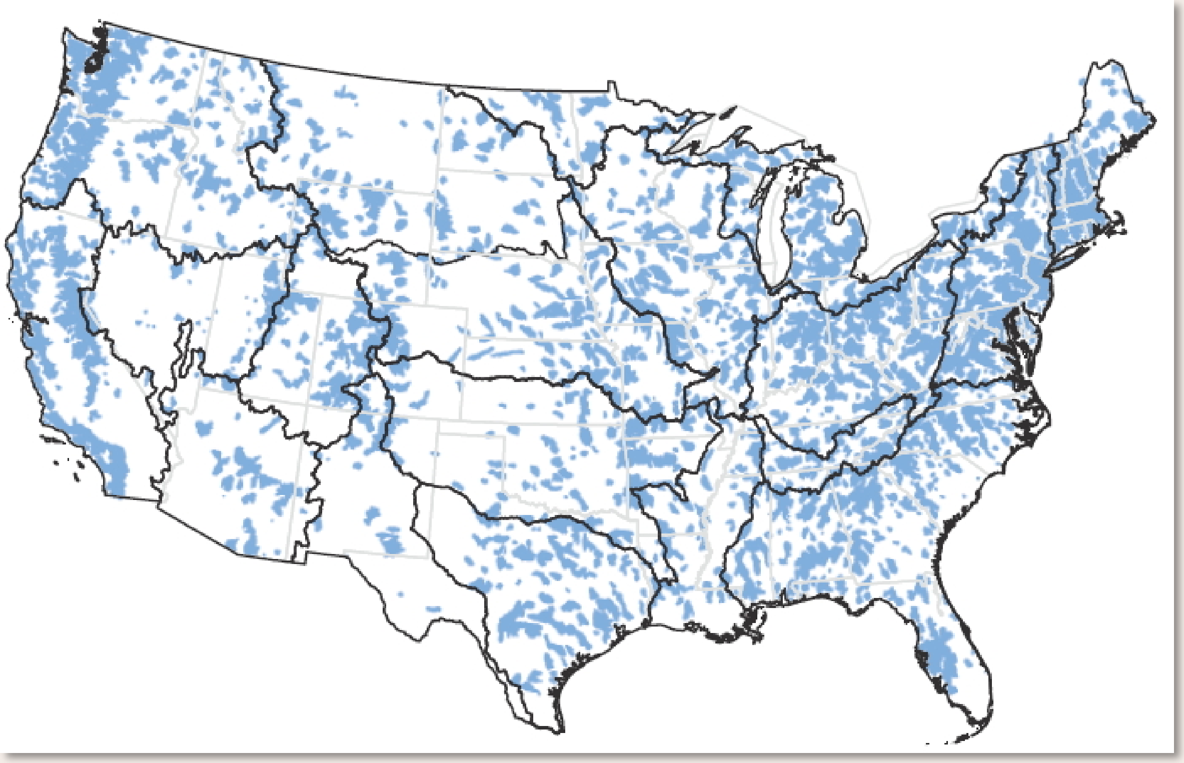


Figure 5.13

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

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

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

Streamflow observations in the Colorado River Basin

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

Figure 5.14

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

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

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

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

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

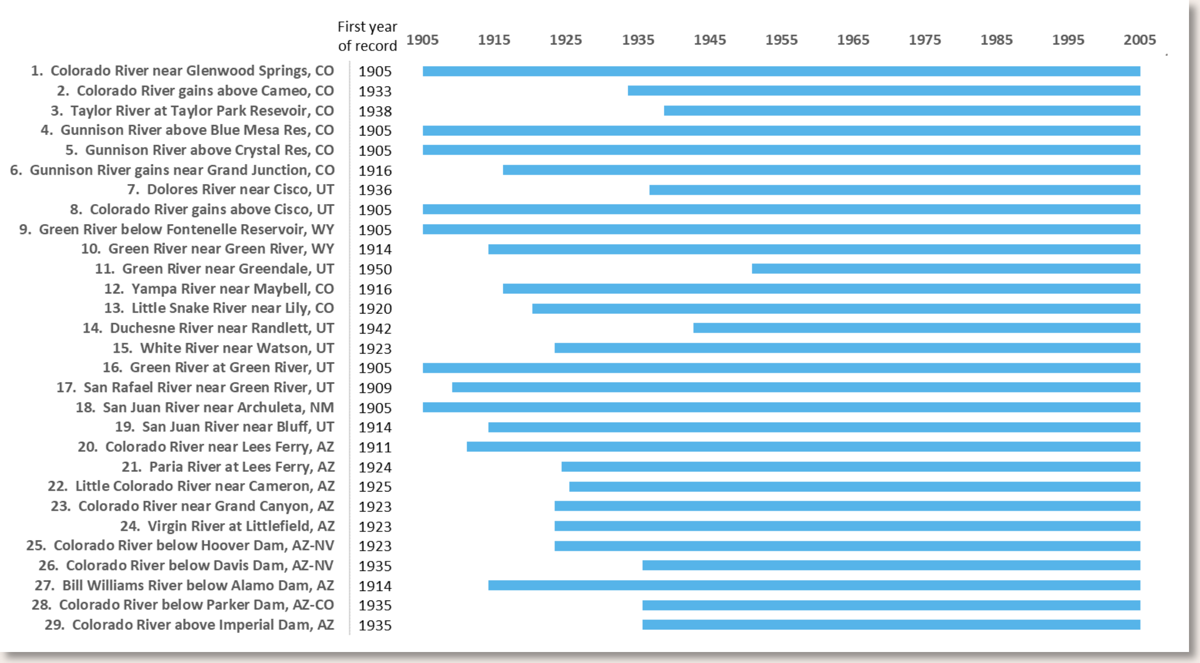
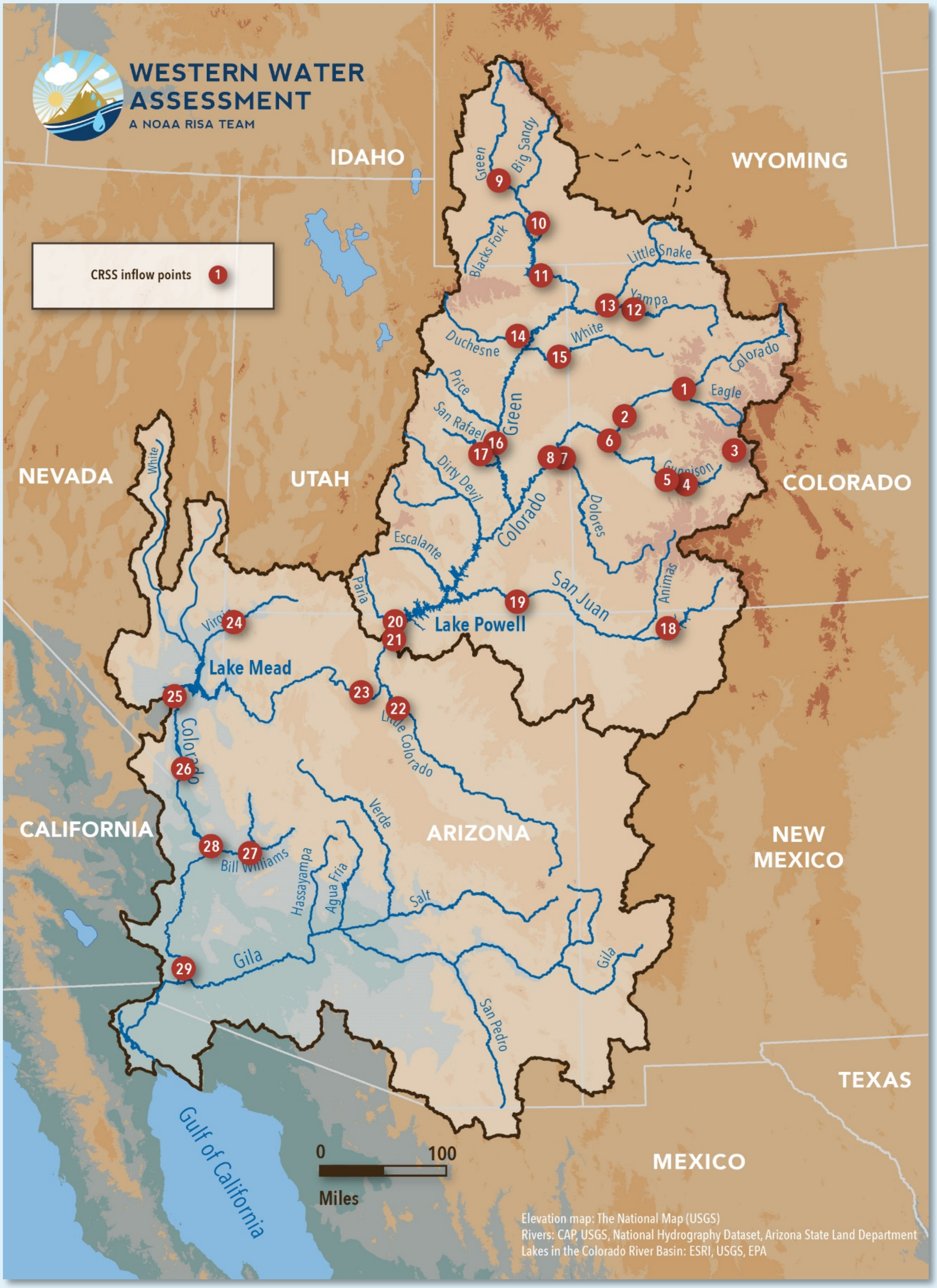


Figure 5.15

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



Elevation map: The National Map (USGS)
Rivers: CAP, USGS, National Hydrography Dataset, Arizona State Land Department
Lakes in the Colorado River Basin: ESRI, USGS, EPA

Figure 5.16

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

Naturalized and unregulated flows

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

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

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

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

Table 5.2

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

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

State of Colorado baseflows

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

UCRC virgin flows

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

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

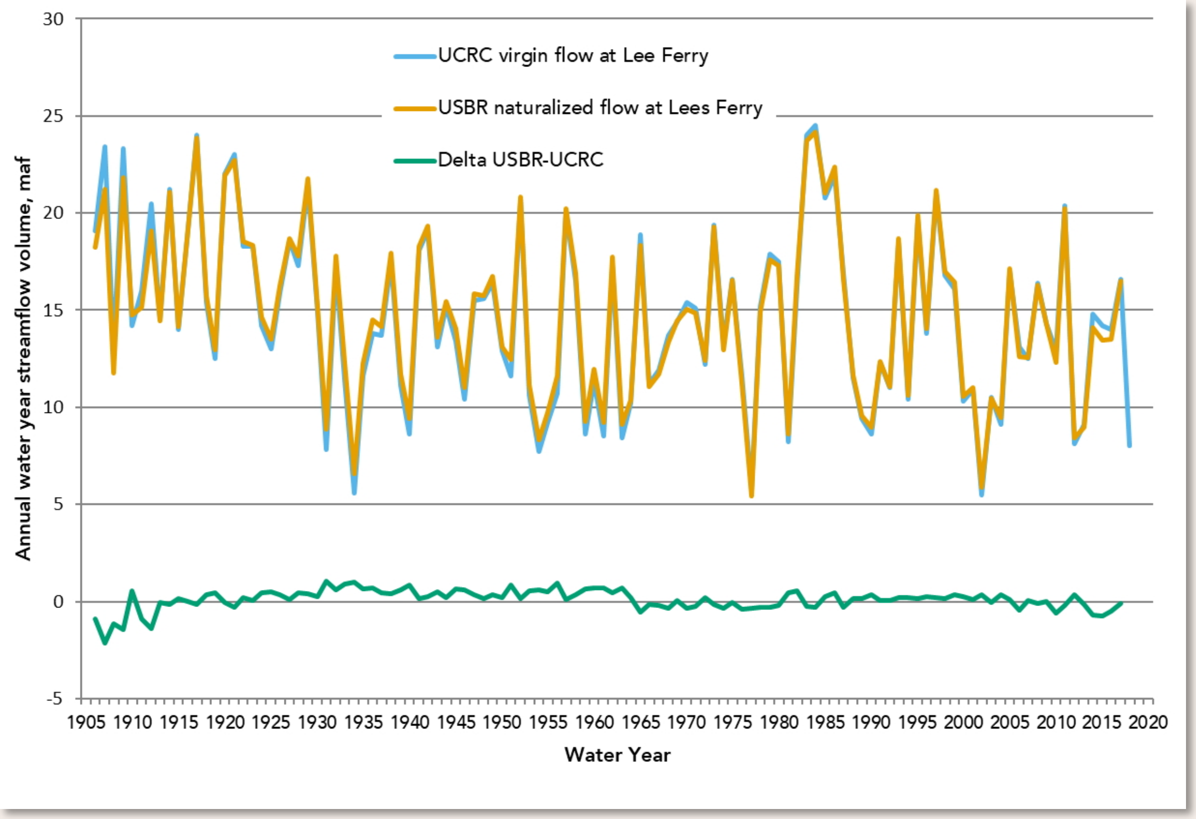


Figure 5.17

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

Reclamation natural flows

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

USBR Colorado River Basin Natural Flow and Salt Data

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

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

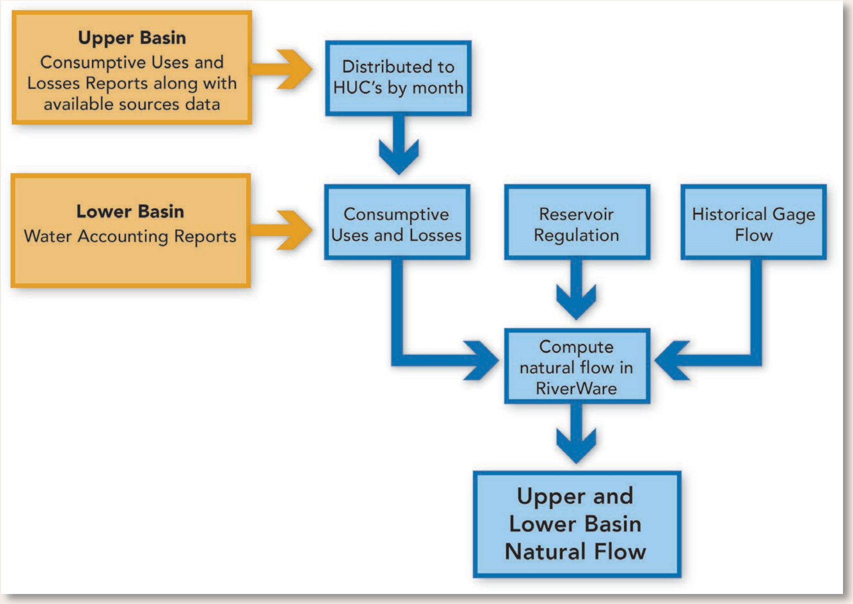


Figure 5.18

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

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

Table 5.3

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

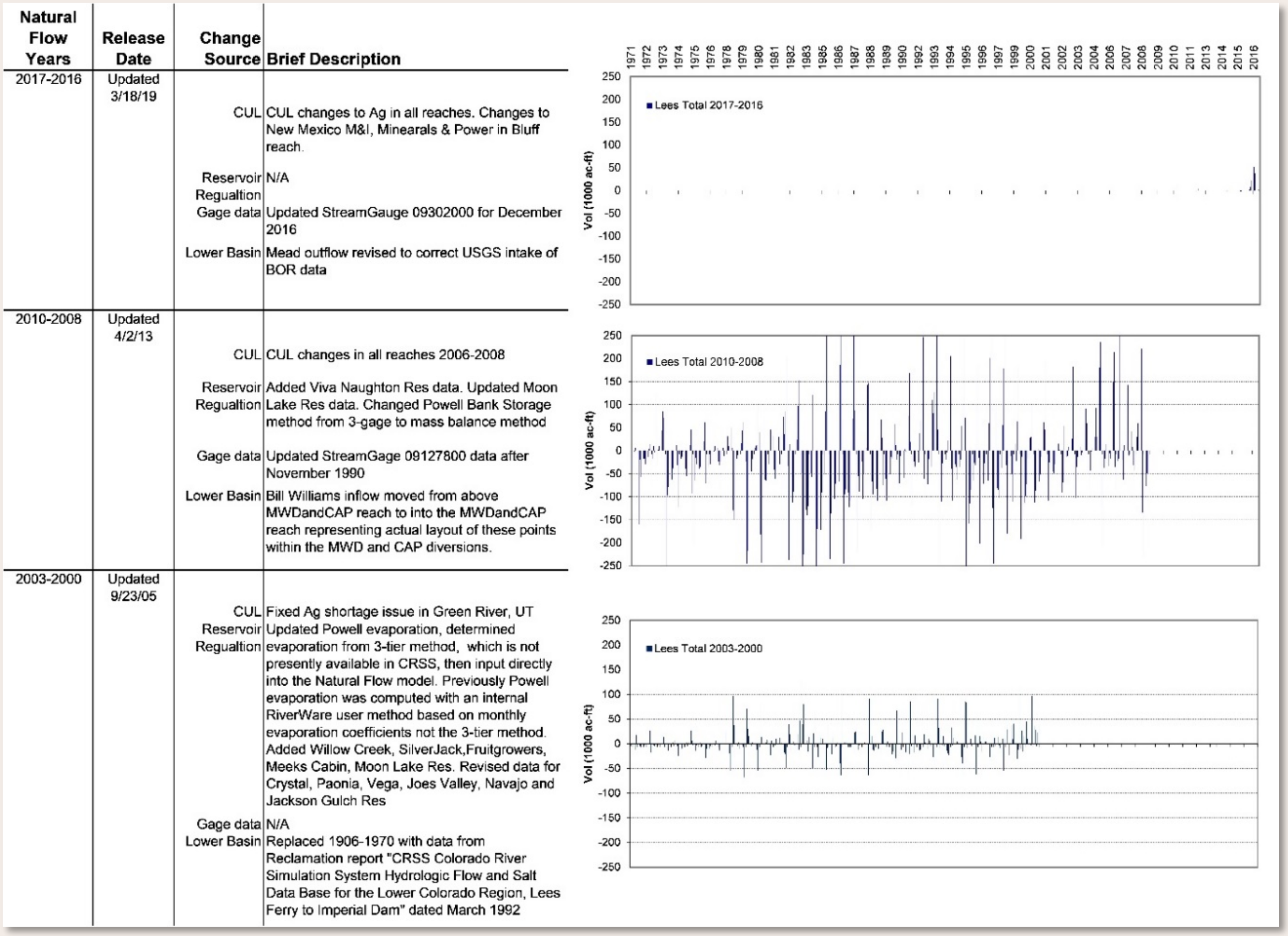
USGS gaging station number	Station name	CRSS inflow point
Was 09072500 Current 09085100-09085000	Colorado River at Glenwood Springs, Colorado	1
09095500	Colorado River near Cameo, Colorado	2
09109000	Taylor River below Taylor Park Reservoir, Colorado	3
09124700	Gunnison River above Blue Mesa Reservoir,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

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

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

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

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



Natural Flow Years	Release Date	Change Source	Brief Description
2017-2016	Updated 3/18/19	CUL	CUL changes to Ag in all reaches. Changes to New Mexico M&I, Minearals & Power in Bluff reach.
		Reservoir Regualtion	N/A
		Gage data	Updated StreamGauge 09302000 for December 2016
		Lower Basin	Mead outflow revised to correct USGS intake of BOR data
2010-2008	Updated 4/2/13	CUL	CUL changes in all reaches 2006-2008
		Reservoir Regualtion	Added Viva Naughton Res data. Updated Moon Lake Res data. Changed Powell Bank Storage method from 3-gage to mass balance method
		Gage data	Updated StreamGage 09127800 data after November 1990
		Lower Basin	Bill Williams inflow moved from above MWDandCAP reach to into the MWDandCAP reach representing actual layout of these points within the MWD and CAP diversions.
2003-2000	Updated 9/23/05	CUL	Fixed Ag shortage issue in Green River, UT
		Reservoir Regualtion	Updated Powell evaporation, determined evaporation from 3-tier method, which is not presently available in CRSS, then input directly into the Natural Flow model. Previously Powell evaporation was computed with an internal RiverWare user method based on monthly evaporation coefficients not the 3-tier method. Added Willow Creek, SilverJack,Fruitgrowers, Meeks Cabin, Moon Lake Res. Revised data for Crystal, Paonia, Vega, Joes Valley, Navajo and Jackson Gulch Res
		Gage data	N/A
		Lower Basin	Replaced 1906-1970 with data from Reclamation report "CRSS Colorado River Simulation System Hydrologic Flow and Salt Data Base for the Lower Colorado Region, Lees Ferry to Imperial Dam" dated March 1992

Figure 5.19

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

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

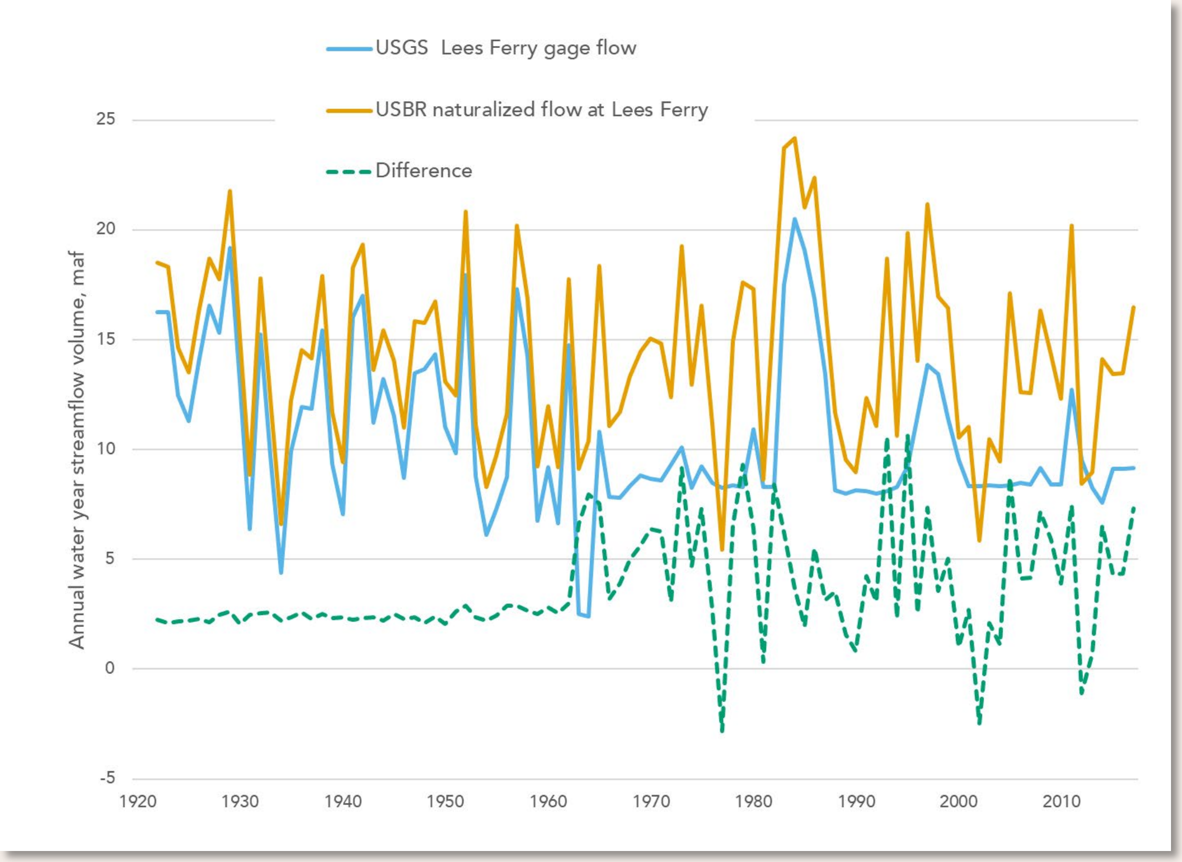


Figure 5.20

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

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

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

Table 5.4

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

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

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

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

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

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

Table 5.5

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

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

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

Natural flow record extension

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

CBRFC unregulated flows

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

Unregulated flow = Observed flow + Diversions + Exports – Imports ± Change in Storage

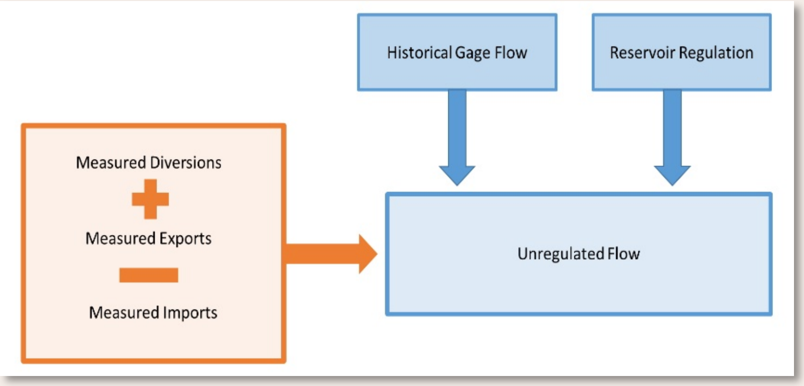


Figure 5.21

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

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

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

Reclamation unregulated flows

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

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

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

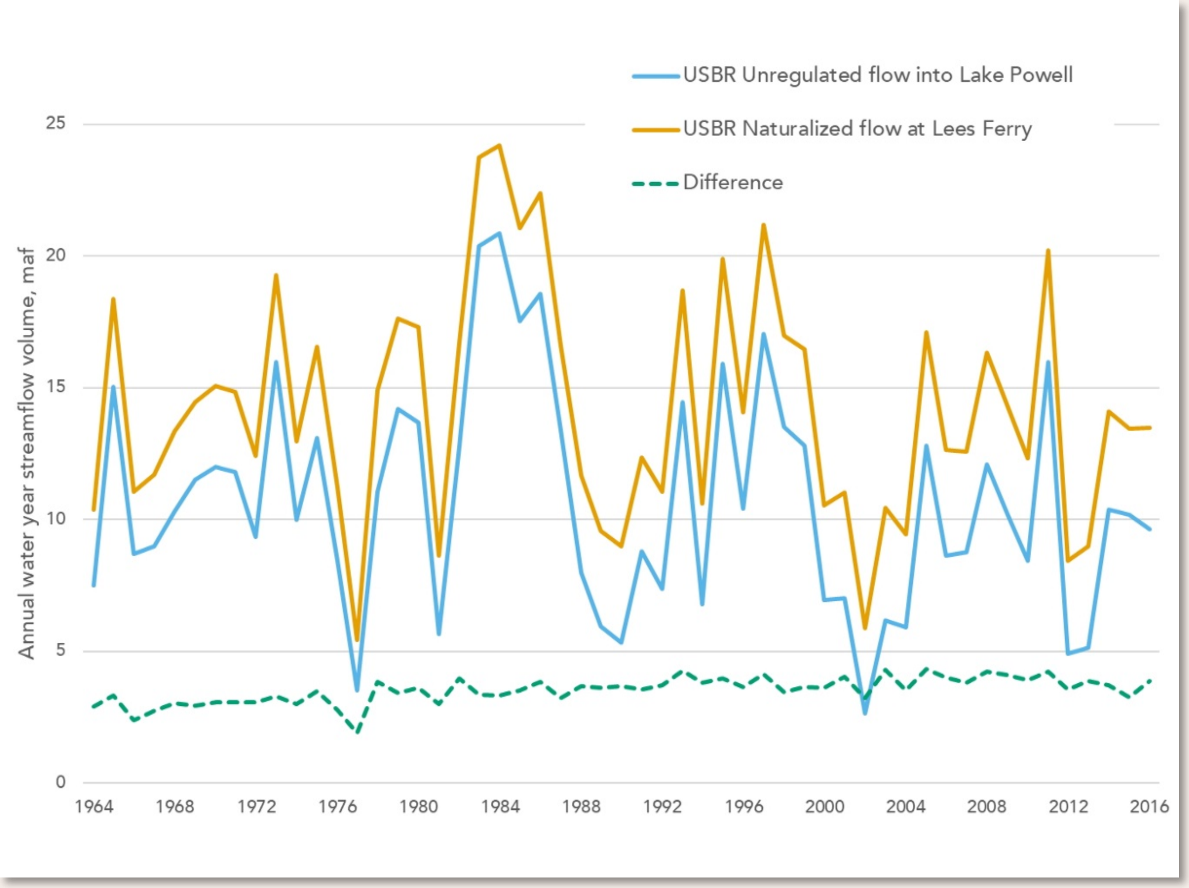


Figure 5.22

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

5.4 Soil moisture observations and monitoring

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

Antecedent fall soil moisture is an important influence on runoff efficiency for the following spring, and thus a soil-moisture term is included in the CBRFC streamflow forecast model. Anomalously low antecedent soil moisture will reduce the forecasted seasonal streamflow, especially for the early season forecasts (December and January) because there is less information then about the snowpack; at those times, forecasted flows are reduced by about 7–10% per 10% departure from normal soil moisture conditions (P. Miller, pers. comm.). Until 20 years ago, in situ observations of soil moisture in the Colorado River Basin were extremely sparse. The density of in situ soil moisture observations in the basin has increased in recent decades, but the spatial representativeness of the point observations is still problematic for basin-wide applications. Accordingly, CBRFC uses modeled soil moisture in their streamflow forecasting. CBRFC has found that only the deepest in situ soil moisture measurements, at about 1 m, correlate with their modeled soil moisture, and many in situ sites do not have sensors at that depth. New remotely sensed data on soil moisture from satellites have the potential to augment and better tie together in situ and modeled soil moisture data, though most remotely sensed data only extend through the top layer (roughly 10 cm) of soil (Table 5.6).

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

In situ soil moisture measurements

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

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

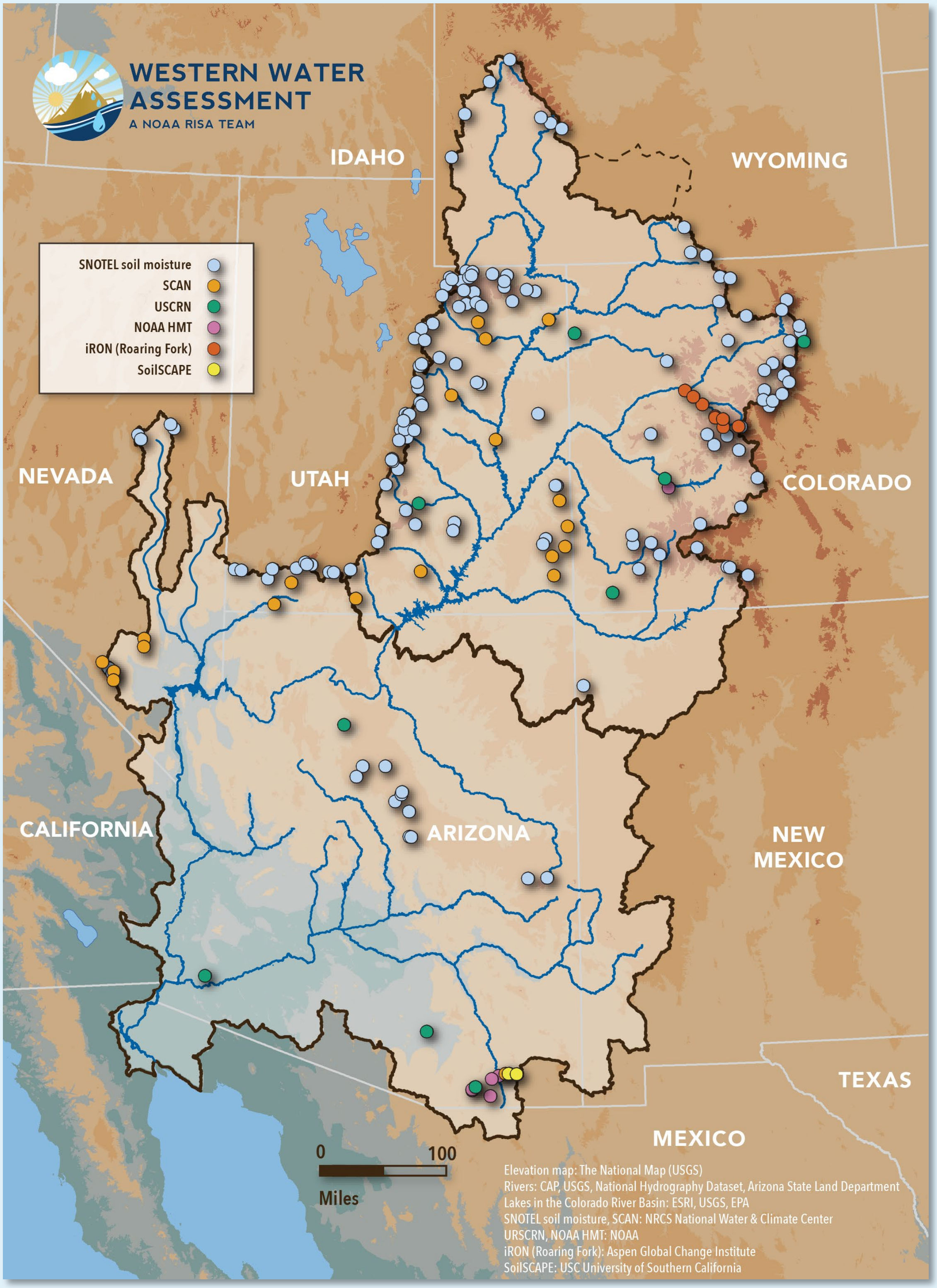
International Soil Moisture Network

Link:
https://www.geo.tuwien.ac.at/insitu/data_viewer/

Table 5.6

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

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



Elevation map: The National Map (USGS)
Rivers: CAP, USGS, National Hydrography Dataset, Arizona State Land Department
Lakes in the Colorado River Basin: ESRI, USGS, EPA
SNOTEL soil moisture, SCAN: NRCS National Water & Climate Center
URSCRN, NOAA HMT: NOAA
iRON (Roaring Fork): Aspen Global Change Institute
SoilSCAPE: USC University of Southern California

Figure 5.23

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

Modeled soil moisture

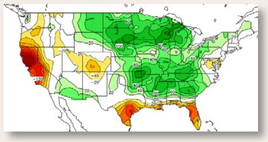
Because of the scarcity of both in situ and remotely sensed soil moisture data, real-time soil moisture conditions have generally been modeled, using observed meteorological inputs—primarily temperature and precipitation, but also humidity and solar radiation in some cases.

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

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

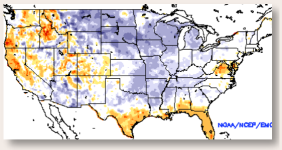
Modeled soil moisture provides much more spatially distributed information than point in situ observations; however, the modeled data also inherit the uncertainties in the underlying meteorological observations, particularly precipitation (Chapter 4), as well as uncertainties in the parameterization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

NOAA Soil Moisture



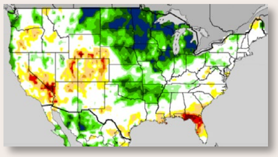
Link: https://www.cpc.ncep.noaa.gov/products/Soilmst_Monitoring/US/Soilmst/Soilmst.shtml

NLDAS Soil Moisture



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

UCLA Soil Moisture



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

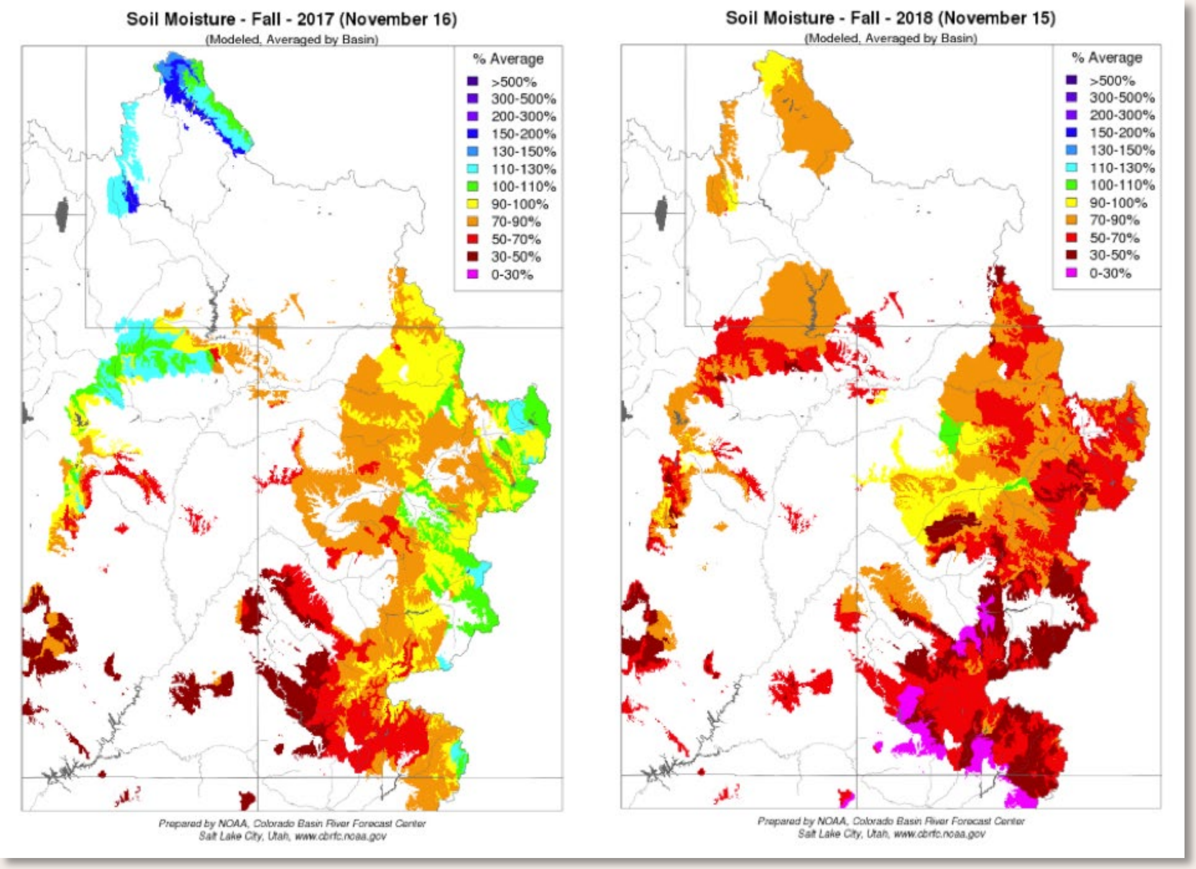


Figure 5.24

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

Remotely sensed soil moisture

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

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

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

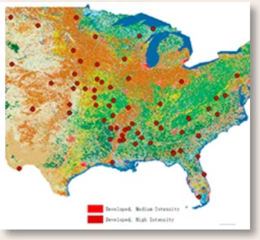
Root zone soil moisture can also be assessed using other satellite derived products that use remotely sensed “land skin” temperature and an energy-balance model to assess the evaporative response from land. The Evaporative Stress Index (ESI; Anderson et al. 2011) is a 4-km spatial resolution data product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

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

National Soil Moisture Network

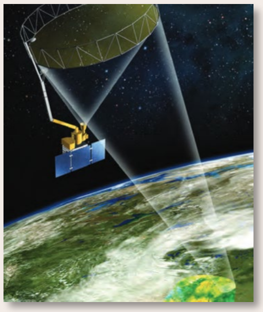
The National Soil Moisture Network (NSMN) is an ongoing multi-agency and multi-university effort that aims to integrate soil moisture data from the several existing in situ monitoring networks throughout the United States, and also to merge these data with modeled and remotely sensed soil moisture products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

NASA SMAP Data



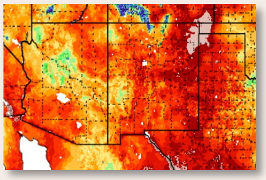
Link: https://nsidc.org/data/smap/smap-data.html

SMAP Sentinel-1



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

NASA SPoRT Center



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

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

5.5 Evaporation, evapotranspiration, and evaporative demand

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

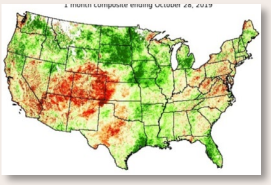
Generally, evaporation-related variables are estimated using a model driven by meteorological observations, or are derived from remote sensing data. Direct in situ observations of these variables (e.g., pan evaporation) are very sparse and do not offer an adequate spatial representation at the watershed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

Monitoring of open-water evaporation

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

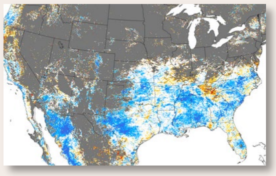
The bulk aerodynamic, or mass transfer, method is arguably the most cost-effective approach for near real-time operational monitoring. From 1955–1994, the USGS calculated evaporation at Lake Mead using the mass transfer method, and from 1965–1979, Reclamation calculated evaporation at Lake Powell using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

USDA Evaporative Stress Index



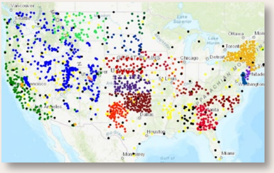
Link: https://hrsl.ba.ars.usda.gov/drought/index.php

Landscape Evaporative Response Index



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

National Soil Moisture Network



Link: http://nationalsoilmoisture.com/

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

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

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

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

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

Figure 5.25
Evaporation monitoring platform located in Padre Bay at Lake Powell, part of a joint study between Reclamation and the Desert Research Institute (DRI). Sensors measuring wind speed and other weather parameters along with water temperature will allow intercomparison of multiple methods for estimating reservoir evaporation. (Image: DRI.)

Monitoring of evapotranspiration

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

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

Table 5.7

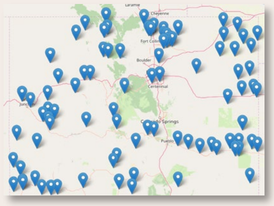
Summary of evapotranspiration and evaporative demand data available over some or all of the Colorado River Basin. See the text for further description of most of these networks and products.

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

Reference crop ET estimations

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

CoAgMET



Link:
https://coagmet.colostate.edu/

Climate Engine

Link:
https://app.climateengine.org/climateEngine

Land surface modeling

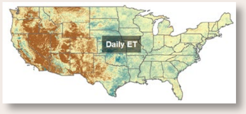
Real-time and gridded ET (AET) estimates are also available from land surface/hydrology models that are driven by observed meteorological forcings. The North American Land Data Assimilation System Phase 2 (NLDAS-2) project provides ET data at hourly or daily timescales at 12 km (7 mile) spatial resolution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

Remote sensing

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

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

US SSEBop Evapotranspiration



Link:
https://earlywarning.usgs.gov/ssebop/modis

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

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

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

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

Open ET

Link:
https://etdata.org/

Monitoring of evaporative demand

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

In situ

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

Modeled

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

CPC Evaporation Data
Link:
https://www.cpc.ncep.noaa.gov/products/GIS/GIS_DATA/JAWF/

ESRL Evaporative Demand Drought Index
Link:
https://www.esrl.noaa.gov/psd/eddi/

5.6 Other remotely sensed hydrologic data relevant to the basin

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

Table 5.8

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

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

Remote sensing of vegetation type/moisture content/irrigated area

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

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

GRACE: Terrestrial water storage change

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

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

More recent studies have compared the water budget for the basin derived from GRACE with water budgets from land-surface models and other hydrology models, finding that GRACE shows larger annual fluxes of water than the models. These GRACE-model differences in the Colorado River Basin are not as large, however, as in many other basins around the world (Scanlon et al. 2018).

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

SWOT: Runoff and water elevation

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

5.7 Challenges and opportunities

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

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

Challenges: Snow

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

Opportunities

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

Challenges: Streamflow

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

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

Opportunities

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

Challenges: Soil moisture and evaporation

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

Opportunities

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

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

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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**