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

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

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

Chapter 3 provides a detailed overview of the three primary Reclamation operations and planning models that support basin decision making. It describes the underlying configurations, assumptions, and applications of the three models. The chapter details how these models use observational data, streamflow forecasts, and planning hydrologies as a prelude to the discussion of those inputs in subsequent chapters.
Chapter 2

Current Understanding of Colorado River Basin Climate and Hydrology

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Key points

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

2.1 Introduction

Describing the spatial and temporal variability of the Colorado River Basin’s hydroclimate, and recent trends in hydroclimate, can help frame expectations of future basin hydrology even before consulting the tools explicitly designed for forecasting and projection. It also provides context for the different datasets and modeling platforms that are considered in
much greater detail in later chapters. Understanding the physical mechanisms that drive basin climate and hydrology, and their links with the global climate system, can also help identify and understand issues with the output of both hydrology models (Chapter 6) and global climate models (Chapter 11).

2.2 Overview of the basin

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

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

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

Figure 2.1
Colorado River Basin observed average annual temperature (upper left), observed average annual precipitation (upper right), modeled average annual runoff (lower right) and modeled annual average runoff efficiency, over the 1981-2010 period. (Data: Livneh et al. 2013; the average temperature and precipitation patterns shown are nearly identical to those seen in the PRISM and gridMet datasets. See Chapter 4 for discussion of these and other gridded climate datasets.)
Table 2.1

<table>
<thead>
<tr>
<th>Basin or Sub-basin (gage)</th>
<th>Natural Streamflow (maf)</th>
<th>Proportion of Colorado River at Imperial Runoff (%)</th>
<th>Precipitation (maf)</th>
<th>Runoff Efficiency (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Green River (nr Green River, UT)</td>
<td>5.4</td>
<td>34%</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Colorado River (nr Cisco, UT)</td>
<td>6.8</td>
<td>42%</td>
<td>92 maf</td>
<td>16%</td>
</tr>
<tr>
<td>San Juan River (nr Bluff, UT)</td>
<td>2.1</td>
<td>13%</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Total Upper Basin (Colorado River at Lees Ferry)</strong></td>
<td><strong>14.8</strong></td>
<td><strong>92%</strong></td>
<td><strong>78 maf</strong></td>
<td><strong>3%</strong></td>
</tr>
<tr>
<td>Inflows between Powell and Mead</td>
<td>0.8</td>
<td>5%</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Inflows between Mead and Imperial Dam</td>
<td>0.4</td>
<td>3%</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Total inflows between Powell and Imperial Dam</td>
<td>1.3</td>
<td>8%</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Total Colorado River above Imperial Dam</strong></td>
<td><strong>16.1</strong></td>
<td><strong>100%</strong></td>
<td><strong>170 maf</strong></td>
<td><strong>10%</strong></td>
</tr>
<tr>
<td>Gila River (nr Dome, AZ at mouth)</td>
<td>1.1</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Total Colorado River at Yuma, AZ</strong></td>
<td><strong>17.2</strong></td>
<td></td>
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</tr>
</tbody>
</table>
Because the vast majority of basin-wide runoff comes from mountain headwaters that are mainly restricted to the periphery of the Upper Basin, the assessment of past variability and likely future changes in Colorado River hydrology will be more meaningful if focused on these headwaters areas. However, these critical mountain areas have fewer and shorter observational records, and are more difficult to represent in models than the more extensive low- and mid-elevation regions of the basin.

2.3 Moisture sources, storm tracks, and seasonality of precipitation

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

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

Starting off the water year, October is usually a transitional month as the atmospheric patterns characteristic of winter emerge. Rapid cooling in the Arctic drives increasingly large north-south contrasts in temperature between the tropics and the polar regions. This temperature contrast both strengthens the prevailing westerly winds and promotes the development of mid-latitude cyclonic storms and other disturbances. The core of the upper-level westerly winds, the polar jet stream, also shifts southward at this time. Storms preferentially form along the jet stream’s path, and then tend to follow that path eastward, so the “storm track” or preferred pathway for storms is largely determined by the jet stream’s location throughout the cool season.
Figure 2.2
Average monthly precipitation (1981–2010) for the Upper Basin and headwaters of the Lower Basin. See text for description of the seasonally varying processes that contribute to these patterns. (Source: PRISM 800-m gridded data http://prism.oregonstate.edu; maps were generated by the Western Regional Climate Center https://wrcc.dri.edu/Climate/prism_precip_maps.php).
The position and activity of the storm track from October through May is the critical climatic driver of annual precipitation in the basin’s headwaters, and thus of annual runoff. A single winter storm may bring 5–10% of annual precipitation to portions of the Upper Basin headwaters, so the occurrence of a handful of strong storms can make the difference between a drought year and a normal runoff year for the basin, or between a normal year and a wet year (Bolinger, Kummerow, and Doesken 2014). While individual storms move across the basin in 1–2 days, the storm track that they follow may persist in one location for several days to a few weeks.

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

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

In mid to late summer (July–September), intense heating of the land surface of northern Mexico and the Southwest induces a shift in the prevailing winds to southerly, drawing moist subtropical air northward. This pattern is known as the North American Monsoon or NAM (Adams and Comrie 1997; Sheppard et al. 2002). The often-daily convective storms associated with the NAM primarily affect the Lower Basin, with nearly all locations in Arizona and western New Mexico receiving 35–50% of the annual precipitation during the July–September period (Sheppard et al. 2002). As the intrusion of the NAM moisture plume advances northward in late
summer, the southern half of the Upper Basin sees increasing convective activity and precipitation as well (Jana et al. 2018). During the late summer and fall, landfalling Pacific tropical cyclones bring additional substantial moisture to the Lower Basin in some years (Hereford and Webb 1992). The net effect of these typical seasonal spatial patterns (Figure 2.2) is that different parts of the basin have characteristic precipitation seasonality, reflecting both north-south and elevational gradients (Sheppard et al. 2002; Lukas et al. 2014).

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

2.4 Influence of topography and elevation

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

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

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

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

2.5 The basin’s snowmelt-dominated hydrology

As indicated in the previous discussion, a disproportionate share of basin-wide precipitation falls in the high-elevation headwaters, where it also falls primarily as snow (Figure 2.3). These cooler mountain areas see lower fractional ET losses in all seasons, and precipitation falling as snow is less prone to ET losses than rain, particularly when falling on a snowpack surface and insulated from ground warmth. Accordingly, like most other basins in the western U.S., the primary component of runoff in the Colorado River Basin is snowmelt. Multiple studies have estimated the contribution of snowmelt to annual streamflow for portions, or all, of the mountainous West ranging from 60% to 85%, as compiled in Li et al. (2017). The most recent West-wide modeling analysis estimated that the contribution of snowmelt to total Upper Basin runoff is 71%, with a higher fraction (>80%) in the high-elevation headwaters sub-basins (Li et al. 2017).
For comparison, just about 50% of the total Upper Basin precipitation falls as snow (Rumsey et al. 2015); thus, the snow fraction of basin-wide annual precipitation has over twice the runoff efficiency of the rain fraction.

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

The basin’s snowpack accumulates over a 4– to 7-month period, with accumulation typically beginning in October at higher elevations in the Upper Basin, and beginning increasingly later in the fall or winter as one...
moves downslope and southward in the basin. The winter climate (November–March) in the Upper Basin is colder than in the other mountain regions of the western U.S. (Lute, Abatzoglou, and Hegewisch 2015) and so the snowpack is less prone to melt loss prior to the spring peak. The peak SWE value in wind-sheltered locations at high elevations (e.g., SNOTEL sites, Chapter 5) typically averages 15”–50” in the Upper Basin, and 3”–10” in the Lower Basin (Figures 2.3 and 2.4).

Field studies and modeling suggest that the equivalent of 10–20% of peak SWE over the basin is lost to sublimation—the transition of water from solid phase directly to gaseous phase—during the course of the season (Hood, Williams, and Cline 1999; Phillips 2013; Hultstrand and Fassnacht 2018). The highest losses occur during the spring months (March–May) when air...
temperatures and shortwave (solar) radiation are higher. The meltout of the snowpack occurs over 1-2 months, much faster than accumulation. Snowmelt typically begins in earnest in February or March in the Lower Basin, and in April or May in the Upper Basin. Snowmelt is driven primarily by greater shortwave radiation due to higher sun angles and longer days, though warmer air temperatures, especially above-freezing air temperatures at night, prime the snowpack for faster melt.

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

The dominance of snowmelt in driving annual runoff is clearly expressed in the shape of the annual hydrograph for all streams and rivers in the Upper Basin, and for many streams and rivers in the Lower Basin as well. Figure 2.5 shows the long-term average hydrograph for natural flows at Lees Ferry for the 1906–2017 period, compared with the annual hydrographs for the lowest-flow year (1977) and the highest-flow year (1984) on record. All three traces show low flows in winter and early spring, the rise to a May/June peak, and declining limb in summer and early fall. (Data: Reclamation, after Prairie and Callejo 2005)
Ferry, with the characteristic rapid rise in spring with snowmelt, a peak typically in May or June, and an equally steep declining limb back to baseflows by late summer. About 70% of the annual flow, on average, occurs during the April–July period typically used for seasonal water supply forecasting, while over 80% of the annual flow occurs during a longer period (March–August) that is more inclusive of snowmelt processes.

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

2.6 Groundwater and surface water

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

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

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

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

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

Interannual variability

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

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

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

Temperature does covary with precipitation during the warm season (i.e., dry April–September periods tend to also be warmer than normal, and wet April–September periods tend to also be cooler than normal). Also, temperature has an independent influence on streamflow, as will be detailed later in this chapter. Even so, precipitation is the most important driver of interannual streamflow variability in the basin, by a wide margin (Nowak et al. 2012; Woodhouse et al. 2016; McCabe et al. 2017), which makes it challenging to accurately assess the role of other factors, such as temperature or antecedent (previous fall) soil moisture.
A common measure of the magnitude of interannual variability in a time-series is the coefficient of variation (CV), which is the ratio of the standard deviation to the mean. A higher CV indicates greater variability. The CV of annual precipitation is 0.16 in the Upper Basin, and slightly higher in the Lower Basin (Table 2.2). As noted above, the variability of annual streamflow is higher than that of precipitation; the CV of Upper Basin (Lees Ferry) annual natural streamflow (1906–2016) is 0.29. This is greater than for annual streamflow of the Columbia River (CV: 0.18; Vano, Das, and Lettenmaier 2012) but similar to the median CV (0.31) of the annual streamflow of 1,221 rivers in a global database (McMahon et al. 2007). Variability in annual streamflow is much higher in the Lower Basin compared to the Upper Basin, because the warmer climate and greater fractional ET losses further accentuate the variability in precipitation. For example, Little Colorado River annual gaged streamflow has a CV of 0.73 (1906–2016), comparable to the CV for the relatively unimpaired headwaters of the Salt River, which share a watershed divide with the Little Colorado. The interannual variability in streamflow itself varies in magnitude over time (Pagano and Garen 2005).
Table 2.2
Variability and persistence in basin precipitation and streamflow over the 1906–2016 period. See text for explanation of indices. (Data: runoff from Reclamation, after Prairie and Callejo (2005); precipitation from NOAA NCEI)

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

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

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

Decadal-scale and longer variability
While the large storage capacity of Colorado River Basin reservoirs buffers the system from many impacts of extreme annual variability (e.g., the record low flow year of 1977), departures from average conditions over several years and longer can accumulate into deficits of 20 to 40 maf that heavily deplete system storage, as with the most recent period. Thus, it is important to consider decadal-scale variability in basin precipitation and streamflow, which can be very simply depicted by a 10-year running average on the annual values, as in Figure 2.7 for Upper Basin streamflow.
Over the observed Lees Ferry record, the 10-year running average has varied by about +/-20% of the long-term average streamflow, with peaks above 18 maf in the 1920s and 1980s, and low points of 12.0–12.5 maf in the 1960s and 2000s. The longest excursions away from the long-term average have been on the order of 20–30 years, and occurred roughly around 1906–1930 (above), 1955–1980 (below), and 2000–2019 (below). With so few of these excursions to examine, it is difficult to say from the observed record alone if the 25-year period of 17–18 maf at the beginning of the record is unusual behavior for the system; however, as described below, tree-ring data suggests that it is unusual.

Another way of examining decadal-scale variability is to use a weighted smoothing filter that emphasizes the values occurring in the middle of the smoothing period. This will make apparent any cyclical behavior that has a wavelength similar to the smoothing period. Figure 2.7 shows a 9-year weighted filter applied to the Lees Ferry streamflow record. While the filtered record stays close to the running average for most of the record, after 1980 the filtered record departs from the running average and shows stronger peaks and troughs up through the late 2000s. This quasi-decadal oscillation after 1980 was also seen in a wavelet analysis performed by Nowak et al. (2012). They found this oscillation to be the strongest periodic variability at any wavelength in the observed Lees Ferry streamflow record—but it was only active over the most recent three decades of the record.
A much longer perspective on decadal-scale variability in the Upper Basin can be seen in the 10-year running mean of a tree-ring reconstruction of Lees Ferry natural streamflow that spans from the years 762 to 2005 (Figure 2.8; Meko et al. 2007). With this much longer context—about 10 times longer than the observed record—the extended high-flow period from 1906–1930 appears to be quite unusual, with only two prior periods (late 1100s and early 1600s) that appear to be comparable. On the opposite extreme, there appear to be many extended low-flow periods with greater cumulative deficits than the 1955–1980 period, or the current 2000–2018 period. Most notable among these are the low-flow periods of roughly 1865–1905 and 1130–1160. Nowak et al. (2012) also performed a wavelet analysis on a shorter tree-ring reconstruction of Lees Ferry flows (back to 1490) and found that a quasi-decadal oscillation was present only intermittently, for no more than 30–40 years at a time, most prominently in the early 1500s, early 1700s, and mid-1800s.

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

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

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

**El Niño-Southern Oscillation (ENSO)**

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

**Figure 2.10**

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

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

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

Figure 2.11

Typical changes in atmospheric circulation over North America associated with El Niño and La Niña events, and the corresponding regional climate anomalies that are likely to occur. (Source: adapted from NOAA, https://www.climate.gov/news-features/featured-images/how-el-ni%C3%B1o-and-la-ni%C3%B1a-affect-winter-jet-stream-and-us-climate)
In the past decade, a second “flavor” of El Niño event has been identified, with the maximum SST anomalies located in the Central Pacific (CP) in contrast with the Eastern Pacific (EP). In a CP El Niño, compared to traditional EP El Niño events, the winter drying influence on the Pacific Northwest is enhanced, but the winter wetting influence on the Southwest is similar (Yu and Zou 2013). It appears that CP El Niño events have become more common in recent decades (Freund et al. 2019).

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

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

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

For Upper Basin-wide precipitation and streamflows (i.e., Lees Ferry), these opposing tendencies mostly cancel out, and it is hard to discern a clear tendency toward higher Lees Ferry flows in El Niño years and lower flows in La Niña years, even during strong events.
Figure 2.13 shows Lees Ferry water-year natural streamflows corresponding to El Niño (n = 12) and La Niña (n = 12) conditions in the beginning of the water year (i.e., fall) from 1980–2018. There are no meaningful differences in average or median flow between El Niño and La Niña cases, or between those and the ENSO-neutral cases (n = 14). The behavior at the lower tails of the distributions, however, appears more distinct: While there are no annual flows below 10 maf among the El Niño cases (0 of 12), 3 of 12 La Niña cases have flows below 10 maf, as do 4 of 14 ENSO-neutral cases.
Decadal and multi-decadal oscillations

Pacific Decadal Oscillation (PDO)

In the north Pacific, to the north of the ENSO source region in the tropical Pacific, is the home of the Pacific Decadal Oscillation (PDO). The PDO was identified in the mid-1990s as the principal mode of sea-surface temperature variability in the northern Pacific. The PDO’s warm phase has positive (warmer-than-normal, El Niño-like) anomalies in the eastern North Pacific and negative (cooler-than-normal, La Niña-like) anomalies in the central and western North Pacific (Mantua et al. 1997). The main oscillation from warm to cool and back is irregular but usually has a period of 10–40 years, with occasional shorter excursions. The PDO is not a single well-defined physical phenomenon like ENSO, and much of the variation in the PDO may actually be ENSO variability translating to the northern Pacific over longer time scales (Newman, Compo, and Alexander 2003; Newman et al. 2016; Chen and Wallace 2016). The ENSO dipole does appear to be strengthened when PDO is in the same phase as ENSO, so that the Southwest and the Lower Basin have had a stronger wet tendency during
warm PDO + warm ENSO (i.e., El Niño), and a stronger dry tendency during cold PDO + cold ENSO (La Niña) (Gershunov and Barnett 1998; Brown and Comrie 2004; Wise 2010). However, these climate influences of PDO do not appear to be stable over time, which argues against their use in hydroclimate forecasting (McAfee 2014; Wise 2015).

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

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

**The trouble with multi-decadal oscillations**
Studies in the 2000s on the AMO, PDO and other oscillations raised hopes that observations and predictions of the AMO state, as well as PDO, could lead to better seasonal and longer hydroclimate forecasts for the basin (Reclamation 2007c). However, the physical mechanism by which the AMO actually affects conditions in the interior West is unclear, unlike with ENSO (Nowak et al. 2012). Like the PDO, the stability of the AMO’s climate teleconnections over time is questionable. Also as with the PDO, there have been very few cycles of warm and cold phases during the observational
period (since about 1900) to compare with basin hydroclimate indices. Statistical relationships that have been found during the past century may not be representative of future relationships, given the limited number of cases to draw from (Switanek and Troch 2011).

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

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

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

2.9 A closer look at basin drought
Having described the overall hydroclimatic variability in the basin, and the key climatic mechanisms associated with that variability, it is important to take a closer look at the lower tail of the distribution of annual
hydroclimatic conditions (i.e., drought), which is the principal recurrent management challenge for water suppliers.

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

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

In the water supply analysis in Reclamation (2020) a “streamflow deficit” (i.e., drought) was defined as a two-year average flow less than 15 maf at Lees Ferry. The 2-year averaging acknowledges the buffering capacity of system reservoir storage. By this measure, the most severe drought in the observed record was from 2000–2005 (6 years), with a cumulative deficit of 24 maf, exceeding the 7-year droughts in the 1930s and 1960s, in which the deficits were about 18 maf. There was another 6-year drought from 2012–2017, with a cumulative deficit of 13 maf (Figure 2.14). Multi-year streamflow deficits of greater than 10 maf are clearly a recurrent feature of the basin’s hydroclimate, but the period since 2000 appears highly unusual in that it includes two such droughts: the most severe (2000–2005) and the 5th most severe (2012–2017).
Woodhouse (2012) analyzed the atmospheric and oceanic features associated with six multi-year Upper Basin droughts from the 1930s to the 2000s, using a different drought definition than shown in Figure 2.14. Her analysis showed that each extended drought evolves in a unique way. The onset and persistence of some droughts is linked to La Niña events, while in other cases, drought years coincide with El Niño events. Most critically, past multi-year droughts have persisted through a variety of modes of natural variability. A key feature for drought years not associated with La Niña events has been a high-pressure anomaly centered over the Pacific Northwest, which tends to deflect storm tracks away from the Upper Basin.

**Figure 2.14**
The water supply analysis in the “Colorado River Basin Water Supply and Demand Study” (hereinafter “Basin Study”; Reclamation 2012e) examined the streamflow reconstruction by Meko et al. (2007) and compared the distribution of the reconstructed streamflow deficits during the historical period (1906–2005) with the distribution of reconstructed streamflow deficits (droughts) over the entire reconstruction (762–2005). That analysis showed that most droughts are 3 years or shorter (Figure 2.15). The distribution of deficits over the 20th century is similar to the distribution over the entire >1200-year period, except at the tails; i.e., events of very long duration or high severity, or both. Over the full reconstruction period, droughts with estimated durations of greater than 5 years and estimated cumulative deficits of greater than 15 maf were much more frequent than in the 1906–2005 period.

Figure 2.15
Drought characteristics over the most recent century (dashed gray line) from the Meko et al. (2007) tree-ring reconstruction of Lees Ferry natural flows, compared with the full reconstructed period (762–2005; solid black line). The full reconstruction contains extreme droughts with longer durations and larger cumulative deficits, as indicated by increasing divergences at lower exceedance probabilities (<10%). (Source: adapted from Reclamation 2012b)
2.10 Recent hydroclimate trends and likely causes

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

Table 2.3
Summary of recent hydroclimate trends in the Upper Basin and the likely causes of those trends. See text in the sections below for references.

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

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

Temperature

The most conspicuous feature of the observed record of annual temperatures for the basin is the warming trend in recent decades (Figure 2.16), as highlighted in many previous reports and studies (National Research Council 2007; Reclamation 2012e; Nowak et al. 2012). Since 1980, there has been a persistent and statistically significant warming trend of about +0.5°F per decade in both the Upper and Lower Basins, with a total of 2.0°F of warming during the 40-year period of 1980–2019. In the Upper and Lower Basins, and over the entire basin (Figure 2.16), 2009–2018 was the warmest 10-year period in the record, and 2017 was the warmest single year. Of the 20 warmest years on record, 17 have occurred since 1994. While the upward trend has included both warmer and cooler years, every year since 1994—including relatively cool 2019—has been warmer than the 1970–1999 average. The average temperature since 2000 has been 2.0°F warmer than the 20th-century average.
This warming has been observed in all seasons, with seasonal trends (+0.4°F to +0.7°F per decade) similar to those for annual temperatures. Daily maximum temperatures have warmed more (+0.65°F per decade) than the average temperatures (+0.5°F per decade) or the daily minimum temperatures (+0.4°F per decade). It is not clear whether the magnitude of warming has differed between lower and higher elevations within the basin (Lukas et al. 2014).

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

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

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

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

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

In the mid-2000s, several studies reported declining trends in April 1 SWE at most SNOTEL and snow course measurement sites throughout the
western U.S. (Hamlet et al. 2005; Mote et al. 2005; Regonda et al. 2005). These studies linked the declining SWE trends with warming spring temperatures throughout the West, with a key mechanism being an increasing fraction of cold-season precipitation falling as rain instead of snow as temperatures have increased (Knowles, Dettinger, and Cayan 2006). In the Colorado River Basin, declining SWE trends were generally weaker, or mixed with increasing trends, compared to other regions of the western U.S because winter temperatures are well below freezing, reducing the impact of this broader snow-to-rain shift (Hamlet et al. 2005; Knowles, Dettinger, and Cayan 2006). Later analyses specific to western Colorado also found declining trends in April 1 SWE, over the 1978–2007 period (Clow 2010), and over 30-, 50-, and 70-year periods ending in 2012 (Lukas et al. 2014). Clow (2010) partially attributed the decline in April 1 SWE to decreasing winter precipitation observed over the same period, also identifying a role for increasing spring temperatures.

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

To summarize the studies of snowpack in the western U.S. and corresponding conclusions for the Colorado River Basin: (a) April 1 SWE has declined over the past 35–60 years across most of the basin headwaters, and some of these declining trends are statistically significant; (b) at least a portion of the April 1 SWE decline in the basin is attributable to warming temperatures since the late 1970s, with a contribution from the decline in
cool-season precipitation during the most recent decades, which itself is likely due to natural variability; (c) because of the relatively cold winter climate of the Upper Basin’s headwaters, the snowpack is more resistant to warming-related impacts than most other regions of the West, and (d) within each sub-basin, lower elevations have generally seen larger reductions in April 1 SWE than higher elevations.

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

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

As with the trends in April 1 SWE, it is difficult to separate the likely causes of the shift toward earlier snowmelt and runoff. Warming winter–spring temperatures almost certainly have a role, but the decline in cold-season
precipitation since 2000 appears to be an important driver as well. Episodic
dust-on-snow deposition also causes earlier snowmelt and runoff (Chapter
5; Painter et al. 2007; 2010; Deems et al. 2013). Snowpacks in the Upper
Basin have become generally dustier in recent decades, with especially
large effects on snowmelt and runoff timing in the San Juan Basin (Clow,
Williams, and Schuster 2016; Painter et al. 2018).

**Streamflow volumes and runoff efficiency**

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

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

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

As discussed previously in this chapter, the variability in water-year
precipitation is the most important driver of variability in annual
streamflow. The period of reduced Upper Basin flow since the 2000s and
the overall declining trend in flow since the late 1970s has coincided with a
decline in water-year precipitation as described earlier. The consensus of
recent studies is that roughly half or more of the recent low-streamflow anomaly (since 2000) is due to variability and trends in precipitation (Nowak et al. 2012; Udall and Overpeck 2017; C. A. Woodhouse et al. 2016; McCabe et al. 2017; Barsugli and Livneh 2018; Xiao, Udall, and Lettenmaier 2018; Hoerling et al. 2019).

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

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

The warming effect on Upper Basin runoff has also been detected and quantified directly from the observational record, while taking into account the potentially confounding relationship between precipitation and temperature. Regression analysis by Nowak et al. (2012) indicated a 7.5% reduction in annual Upper Basin runoff for every 1°F warming, a larger reduction than shown by any of the hydrologic models. McCabe et al. (2017), using a similar regression analysis, concluded that the impact of warming temperatures on Upper Basin runoff was ~7% for the period from the late
1980s through 2012, which implies a 4–5% reduction in annual runoff per 1°F warming, within the range found with the hydrologic models. Woodhouse et al. (2016) inferred an impact of warm-season temperatures on Upper Basin runoff in recent decades from the increasing differences between the precipitation anomaly and the runoff anomaly, but did not quantify the impact.

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

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

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

• Evapotranspiration rates generally increase with warmer temperatures (Foster et al. 2016; Milly and Dunne 2020).

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

### 2.11 Challenges and opportunities

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

**Challenges**

• There is still considerable uncertainty in the quantification of the relative roles of temperature, precipitation, antecedent soil moisture, dust-on-snow, and vegetation change in recent and ongoing variability and change in Upper Basin snowpack and streamflow.

• These factors have substantial spatial variability, but most studies have conducted analyses and presented findings only at the Upper Basin-wide scale (e.g. Lees Ferry).

**Opportunities**

• Conduct analyses of Upper Basin hydrologic change that are spatially disaggregated at least to the eight major sub-basins (Upper Green, Yampa–White, etc.), or focus only on the most productive headwaters areas, or both.

• Pursue the various pathways to improve hydrologic modeling presented in Chapter 6.

• Conduct intercomparisons of hydrologic models and statistical methods for assessing the factors behind hydrologic changes.


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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

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 (gages) 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.
<table>
<thead>
<tr>
<th>Acronyms &amp; Abbreviations</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>24MS</strong> 24-Month Study Model</td>
</tr>
<tr>
<td><strong>AET</strong> actual evapotranspiration</td>
</tr>
<tr>
<td><strong>AgriMET</strong> Cooperative Agricultural Weather Network</td>
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<tr>
<td><strong>AgWxNet</strong> Agricultural Weather Network</td>
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<tr>
<td><strong>AHPS</strong> Advanced Hydrologic Prediction Service</td>
</tr>
<tr>
<td><strong>ALEXI</strong> Atmosphere-Land Exchange Inversion</td>
</tr>
<tr>
<td><strong>AMJ</strong> April-May-June</td>
</tr>
<tr>
<td><strong>AMO</strong> Atlantic Multidecadal Oscillation</td>
</tr>
<tr>
<td><strong>ANN</strong> artificial neural network</td>
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<tr>
<td><strong>AOP</strong> Annual Operating Plan</td>
</tr>
<tr>
<td><strong>AR</strong> atmospheric river</td>
</tr>
<tr>
<td><strong>AR-1</strong> first-order autoregression</td>
</tr>
<tr>
<td><strong>ARKStorm</strong> Atmospheric River 1,000-year Storm</td>
</tr>
<tr>
<td><strong>ASCE</strong> American Society of Civil Engineers</td>
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<tr>
<td><strong>ASO</strong> Airborne Snow Observatory</td>
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<tr>
<td><strong>ASOS</strong> Automated Surface Observing System</td>
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<tr>
<td><strong>AVHRR</strong> Advanced Very High-Resolution Radiometer</td>
</tr>
<tr>
<td><strong>AWOS</strong> Automated Weather Observing System</td>
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<tr>
<td><strong>BCCA</strong> Bias-Corrected Constructed Analog</td>
</tr>
<tr>
<td><strong>BCSD</strong> Bias-Corrected Spatial Disaggregation (downscaling method)</td>
</tr>
<tr>
<td><strong>BCSD5</strong> BCSD applied to CMIP5</td>
</tr>
<tr>
<td><strong>BOR</strong> United States Bureau of Reclamation</td>
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<tr>
<td><strong>BREB</strong> Bowen Ratio Energy Balance method</td>
</tr>
<tr>
<td><strong>C3S</strong> Copernicus Climate Change Service</td>
</tr>
<tr>
<td><strong>CA</strong> Constructed Analogues</td>
</tr>
<tr>
<td><strong>CADSWES</strong> Center for Advanced Decision Support for Water and Environmental Systems</td>
</tr>
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<td><strong>CADWR</strong> California Department of Water Resources</td>
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<tr>
<td><strong>CanCM4i</strong> Canadian Coupled Model, 4th generation (global climate model)</td>
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<tr>
<td><strong>CBRFC</strong> Colorado Basin River Forecast Center</td>
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<tr>
<td>Acronym</td>
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</tr>
<tr>
<td>CCA</td>
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<td>CCSM4</td>
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<td>CDEC</td>
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<td>GeoTiff</td>
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</table>
GFS  
Global Forecast System model

GHCTN  
Global Historical Climatology Network

GHCTN-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
<table>
<thead>
<tr>
<th>Acronym</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>ICAR</td>
<td>Intermediate Complexity Atmospheric Research model</td>
</tr>
<tr>
<td>ICS</td>
<td>intentionally created surplus</td>
</tr>
<tr>
<td>IDW</td>
<td>inverse distance weighting</td>
</tr>
<tr>
<td>IFS</td>
<td>integrated forecast system</td>
</tr>
<tr>
<td>IHC</td>
<td>initial hydrologic conditions</td>
</tr>
<tr>
<td>INSTAAR</td>
<td>Institute of Arctic and Alpine Research</td>
</tr>
<tr>
<td>IPCC</td>
<td>Intergovernmental Panel on Climate Change</td>
</tr>
<tr>
<td>IPO</td>
<td>Interdecadal Pacific Oscillation</td>
</tr>
<tr>
<td>IRI</td>
<td>International Research Institute</td>
</tr>
<tr>
<td>iRON</td>
<td>Interactive Roaring Fork Observing Network</td>
</tr>
<tr>
<td>ISM</td>
<td>Index Sequential Method</td>
</tr>
<tr>
<td>JFM</td>
<td>January-February-March</td>
</tr>
<tr>
<td>JJA</td>
<td>June-July-August</td>
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<tr>
<td>K-NN</td>
<td>K-Nearest Neighbor</td>
</tr>
<tr>
<td>Landsat</td>
<td>Land Remote-Sensing Satellite (System)</td>
</tr>
<tr>
<td>LAST</td>
<td>Lane’s Applied Stochastic Techniques</td>
</tr>
<tr>
<td>LERI</td>
<td>Landscape Evaporative Response Index</td>
</tr>
<tr>
<td>lidar</td>
<td>light detection and ranging</td>
</tr>
<tr>
<td>LOCA</td>
<td>Localized Constructed Analog</td>
</tr>
<tr>
<td>LSM</td>
<td>land surface model</td>
</tr>
<tr>
<td>M&amp;I</td>
<td>municipal and industrial (water use category)</td>
</tr>
<tr>
<td>MACA</td>
<td>Multivariate Adaptive Constructed Analog</td>
</tr>
<tr>
<td>maf</td>
<td>million acre-feet</td>
</tr>
<tr>
<td>MAM</td>
<td>March-April-May</td>
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<tr>
<td>MEFP</td>
<td>Meteorological Ensemble Forecast Processor</td>
</tr>
<tr>
<td>METRIC</td>
<td>Mapping Evapotranspiration at high Resolution with Internalized Calibration</td>
</tr>
<tr>
<td>MJO</td>
<td>Madden-Julian Oscillation</td>
</tr>
<tr>
<td>MMEFS</td>
<td>Met-Model Ensemble Forecast System</td>
</tr>
<tr>
<td>MOCOM</td>
<td>Multi-Objective Complex evolution</td>
</tr>
<tr>
<td>MODDRFS</td>
<td>MODIS Dust Radiative Forcing in Snow</td>
</tr>
<tr>
<td>Acronym</td>
<td>Definition</td>
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<tr>
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<tr>
<td>MODIS</td>
<td>Moderate Resolution Imaging Spectroradiometer</td>
</tr>
<tr>
<td>MODIS LST (MYD11A2)</td>
<td>Moderate Resolution Imaging Spectroradiometer Land Surface Temperature (MYD11A2)</td>
</tr>
<tr>
<td>MODSCAG</td>
<td>MODIS Snow Covered Area and Grain-size</td>
</tr>
<tr>
<td>MPR</td>
<td>Multiscale Parameter Regionalization</td>
</tr>
<tr>
<td>MRM</td>
<td>Multiple Run Management</td>
</tr>
<tr>
<td>MT-CLIM (or MTCLIM)</td>
<td>Mountain Climate simulator</td>
</tr>
<tr>
<td>MTOM</td>
<td>Mid-Term Probabilistic Operations Model</td>
</tr>
<tr>
<td>NA-CORDEX</td>
<td>North American Coordinated Regional Downscaling Experiment</td>
</tr>
<tr>
<td>NAM</td>
<td>North American Monsoon</td>
</tr>
<tr>
<td>NAO</td>
<td>North Atlantic Oscillation</td>
</tr>
<tr>
<td>NARCCAP</td>
<td>North American Regional Climate Change Assessment Program</td>
</tr>
<tr>
<td>NARR</td>
<td>North American Regional Reanalysis</td>
</tr>
<tr>
<td>NASA</td>
<td>National Aeronautics and Space Administration</td>
</tr>
<tr>
<td>NASA JPL</td>
<td>NASA Jet Propulsion Laboratory</td>
</tr>
<tr>
<td>NCAR</td>
<td>National Center for Atmospheric Research</td>
</tr>
<tr>
<td>NCCASC</td>
<td>North Central Climate Adaptation Science Center</td>
</tr>
<tr>
<td>NCECONET</td>
<td>North Carolina Environment and Climate Observing Network</td>
</tr>
<tr>
<td>NCEI</td>
<td>National Centers for Environmental Information</td>
</tr>
<tr>
<td>NCEP</td>
<td>National Centers for Environmental Prediction</td>
</tr>
<tr>
<td>nClimDiv</td>
<td>new Climate Divisional (NOAA climate dataset)</td>
</tr>
<tr>
<td>NDBC</td>
<td>National Data Buoy Center</td>
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<tr>
<td>NDVI</td>
<td>Normalized Difference Vegetation Index</td>
</tr>
<tr>
<td>NDWI</td>
<td>Normalized Difference Water Index</td>
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<tr>
<td>NEMO</td>
<td>Nucleus for European Modelling of the Ocean (global ocean model)</td>
</tr>
<tr>
<td>NevCan</td>
<td>Nevada Climate-ecohydrological Assessment Network</td>
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<tr>
<td>NGWOS</td>
<td>Next-Generation Water Observing System</td>
</tr>
<tr>
<td>NHMM</td>
<td>Bayesian Nonhomogenous Hidden Markov Model</td>
</tr>
</tbody>
</table>
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

NWRIS
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
<table>
<thead>
<tr>
<th>Acronym</th>
<th>Definition</th>
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<tbody>
<tr>
<td>SCAN</td>
<td>Soil Climate Analysis Network</td>
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<tr>
<td>SCE</td>
<td>Shuffled Complex Evolution</td>
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<tr>
<td>SCF</td>
<td>seasonal climate forecast</td>
</tr>
<tr>
<td>SE</td>
<td>standard error</td>
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<tr>
<td>SECURE</td>
<td>Science and Engineering to Comprehensively Understand and Responsibly Enhance Water</td>
</tr>
<tr>
<td>SFWMD</td>
<td>South Florida Water Management District</td>
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<tr>
<td>SM</td>
<td>soil moisture</td>
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<td>SMA</td>
<td>Soil Moisture Accounting</td>
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<td>SMAP</td>
<td>Soil Moisture Active Passive</td>
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<td>SMHI</td>
<td>Swedish Meteorological and Hydrological Institute</td>
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<td>SMLR</td>
<td>Screening Multiple Linear Regression</td>
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<td>SMOS</td>
<td>Soil Moisture and Ocean Salinity</td>
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<td>SNODAS</td>
<td>Snow Data Assimilation System</td>
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<td>Snow Telemetry</td>
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<td>SOI</td>
<td>Southern Oscillation Index</td>
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<td>SON</td>
<td>September-October-November</td>
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<td>SPoRT</td>
<td>Short-term Prediction Research Transition</td>
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<td>Special Report on Emissions Scenarios</td>
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<td>Salt River Project</td>
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<td>SSEBOP</td>
<td>Simplified Surface Energy Balance</td>
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<td>SSEBOP ET</td>
<td>Simplified Surface Energy Balance Evapotranspiration</td>
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<td>SSP</td>
<td>Societally Significant Pathway</td>
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<tr>
<td>SST</td>
<td>sea surface temperatures</td>
</tr>
<tr>
<td>SSW</td>
<td>stratospheric sudden warming</td>
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<tr>
<td>SubX</td>
<td>Subseasonal Experiment</td>
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<td>SUMMA</td>
<td>Structure for Unifying Multiple Modeling Alternatives</td>
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<tr>
<td>SVD</td>
<td>singular value decomposition</td>
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<tr>
<td>SW</td>
<td>surface water</td>
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<tr>
<td>SWANN</td>
<td>Snow-Water Artificial Neural Network Modeling System</td>
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<td>SWcasts</td>
<td>Southwest Forecasts</td>
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<tr>
<td>Acronym</td>
<td>Definition</td>
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<tr>
<td>SWE</td>
<td>snow water equivalent</td>
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<tr>
<td>SWOT</td>
<td>Surface Water and Ocean Topography</td>
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<td>SWS</td>
<td>Statistical Water Supply</td>
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<td>Tair</td>
<td>air temperature</td>
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<tr>
<td>Tdew</td>
<td>dew point temperature</td>
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<tr>
<td>TopoWx</td>
<td>Topography Weather (climate dataset)</td>
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<tr>
<td>TVA</td>
<td>Tennessee Valley Authority</td>
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<tr>
<td>UC</td>
<td>Upper Colorado Region (Reclamation)</td>
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<tr>
<td>UCAR</td>
<td>University Corporation for Atmospheric Research</td>
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<tr>
<td>UCBOR</td>
<td>Upper Colorado Bureau of Reclamation</td>
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<td>UCRB</td>
<td>Upper Colorado River Basin</td>
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<td>UCRC</td>
<td>Upper Colorado River Commission</td>
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<td>UCRSFIG</td>
<td>Upper Colorado Region State-Federal Interagency Group</td>
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<tr>
<td>USACE</td>
<td>U.S. Army Corps of Engineers</td>
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<tr>
<td>USBR</td>
<td>U.S. Bureau of Reclamation</td>
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<td>USCRN</td>
<td>U.S. Climate Reference Network</td>
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<td>USDA</td>
<td>U.S. Department of Agriculture</td>
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<tr>
<td>USGCRP</td>
<td>U.S. Global Change Research Program</td>
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<td>USGS</td>
<td>U.S. Geological Survey</td>
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<td>USHCN</td>
<td>United States Historical Climatology Network</td>
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<tr>
<td>VIC</td>
<td>Variable Infiltration Capacity (model)</td>
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<td>VIIRS</td>
<td>Visible Infrared Imaging Radiometer Suite</td>
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<td>VPD</td>
<td>vapor pressure deficit</td>
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<td>WBAN</td>
<td>Weather Bureau Army Navy</td>
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<td>WCRP</td>
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<td>Weather Forecast Office</td>
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<td>Western Regional Climate Center</td>
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<td>WRF</td>
<td>Weather Research and Forecasting</td>
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<tr>
<td>WRF-Hydro</td>
<td>WRF coupled with additional models to represent hydrologic processes</td>
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</table>
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