Colorado River Basin Climate and Hydrology
State of the Science

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Volume IV of the Colorado River Basin State of the Science report focuses on models and methods for developing hydrologic traces that represent plausible hydrologic futures and can be run through system or planning models to evaluate the potential for outcomes and impacts of interest over the next 5 to 50 years. The three main approaches for developing such traces are Historical Hydrology (Chapter 9), Paleohydrology (Chapter 10), and Climate Change-informed Hydrology (Chapter 11).

Long-term hydrologies generated using one or more of these approaches are used as driving inputs for Reclamation’s CRSS planning model, as well as similar planning and system models used by other organizations. The three chapters in Volume IV provide comprehensive descriptions and assessments of the respective approaches and their variants, the data they require, their applications, and their tradeoffs. It is important to examine and understand these choices in order to select appropriate hydrologic traces for system modeling and risk, and also to interpret the output of system modeling that has already been performed.

Traditional long-term planning methods are based on the assumption that future hydrology will have characteristics (average, variance, extremes) similar to the historical observed hydrology. The extreme hydrologic drought of 2000–2004, unprecedented in the observed record, highlighted the downside of basing expectations for future hydrology only on the observed record (i.e. historical hydrology). Clearly, hydrologic behavior outside the range of the past 100 years was, and is, possible. Accordingly, the system analyses performed by Reclamation to support the 2007 Interim Guidelines included, for the first time, ensembles of hydrologic traces based on tree-ring reconstructions of basin paleohydrology. These traces show a broader range of natural variability, including more severe and sustained droughts, than those based only on the past century’s observed hydrology (Chapter 2).
As the dry period that began in 2000 persisted, studies modeling the future impacts of human-caused climate change on basin hydrology consistently indicated that the 21st century was likely to see systematic shifts in hydrologic conditions: earlier snowmelt and runoff, lower runoff efficiency, and (with less certainty) a decline in annual streamflow. Because Reclamation and other basin stakeholders saw the need to explicitly represent this additional climate change risk in planning studies, Appendix U in the 2007 Interim Guidelines laid out a pathway for developing and using climate change-informed hydrologic traces. In 2012, the Basin Study formally incorporated a climate change-informed ensemble along with traces based on historical hydrology and paleohydrology, using Robust Decision Making techniques to assess risks from all scenarios on an equal footing.

As with the historical hydrology and paleohydrology, a typical analysis of climate change-informed hydrology will outline an ensemble of potential future trajectories for basin hydrology. Over longer planning horizons (30 years or more), the range depicted by this ensemble is even broader than those depicted by historical hydrology and paleohydrology, most notably on the dry side of the distribution.

Several planning studies for the basin have used hydrologic traces that effectively blend information from two or more types of hydrology; these are described in greater detail within the listed chapters:

- “Paleo-conditioned” hydrology takes state-transition (wet-dry) information and resamples the historical hydrology to create new sequences that reflect paleo-variability (Chapter 10)
- Delta-method statistical downscaling takes future change factors in temperature and precipitation from climate-model ensembles and perturbs the historical climate sequence to simulate the historical hydrologic variability recurring under future climate (Chapter 11)
- Temperature-perturbed hydrology is similar to the above, but uses several prescribed temperature change factors to simulate the historical hydrologic variability recurring under a warmer climate, assuming no precipitation changes (Chapter 11)

While the sequence of the three chapters may suggest an evolution or transition, it would be incorrect to conclude that climate change-informed hydrology is now the preferred or optimal source of long-term traces to drive system models for planning studies. All three main sources of hydrologic ensembles (historical, paleohydrology, climate change-informed) have inherent advantages and limitations, summarized in the table below. These attributes may be more or less relevant depending on the time horizon of a risk assessment. For example, assessing risk five years into the future would not need to account for the sources of future uncertainty that longer-term studies must grapple with. For long-term risk assessments, it is more helpful to base analyses on at least two, and ideally all three types of hydrology, than any single type; more specifically, it is inappropriate to assume the historical hydrology will repeat itself. To further reduce the impacts of the assumptions inherent to any ensemble, it may be beneficial to use advanced analytical and decision-support frameworks that deemphasize probabilistic risk.
Key characteristics of the main types of hydrology, observed, paleohydrology, and climate change-informed. (Source: adapted from Lukas et al. 2014)

<table>
<thead>
<tr>
<th>Most useful information to extract from this type of hydrology</th>
<th>Historical hydrology (Chapter 9)</th>
<th>Paleohydrology (Chapter 10)</th>
<th>Climate change-informed hydrology (Chapter 11)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Variability (interannual to decadal); recent trends</td>
<td>Variability (interannual to multi-decadal); shifts in mean and variability</td>
<td>Potential long-term future changes</td>
</tr>
</tbody>
</table>

| Embedded assumption in using this to inform planning | Historical mean and variability is stable over time and is representative of future risk | Pre-1900 hydrology, including severe droughts and shifts in mean and variability, can recur in the future | Climate models can provide reliable information about future changes in the basin |

| Key data and models | Gaged observations of streamflow and major diversions; water-balance model to naturalize streamflow (except at headwaters gages) | Tree-ring chronologies (site time-series); statistical models relating ring-width to climate and hydrology | Global climate models, statistical downscaling and bias-correction methods; gridded climate data; regional climate models; hydrology models |

| Advantages | Provides baseline information about risk; relates other sources of information to our experience of system impacts; readily available, trusted, and well-vetted | Shows broader range of natural variability than seen in the observed records; places observed variability in longer context; provides many sequences of wet and dry years | Best source of information about potential effects of future climate change on hydrology |

| Limitations | Does not capture the full range of natural variability; does not reflect risk from future climate change; likely to underestimate future system stresses | Uncertainty in the proxy information; does not reflect risk from future climate change, though the broader range of variability may approximate that risk | Larger uncertainties in future changes, requiring consideration of many traces; complex datasets that are difficult to obtain, analyze and interpret |

| Primary sources of uncertainty affecting the output | Imperfect record of streamflows; inadequate characterization of depletions when naturalizing gage records | Tree rings imperfectly reflect hydroclimatic conditions; choices in handling of the tree-ring data and the model that relates tree-ring data to observed streamflows | Future emissions of greenhouse gases; differing climate models; choice of downscaling and bias-correction methods; differing hydrologic models |
Chapter 10
Paleohydrology

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Key points

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

10.1 Introduction to tree-ring reconstructions of streamflow

As outlined in the Volume IV introduction, water resources planning has traditionally been based on observed records of climate and hydrology, which extend up to 120 years into the past, at best. Through the 20th century, the assumption that future Colorado River Basin supply could be represented in planning by the observed hydrology alone went largely untested. However, by the mid-2000s, with the demands for basin water approaching or exceeding supply, rapid declines in reservoir levels due to severe drought, and the growing realization that climate change could result in reduced flows, water agencies increasingly looked to tree-ring reconstructions of paleohydrology for additional perspective on water supply risk.

Tree-ring reconstructions of streamflow are based on moisture-limited trees that provide a proxy record of hydroclimatic variability. The annual ring widths in these trees correspond primarily to variations in moisture, particularly if they are growing on open, south-facing slopes with thin soils, where competition from other trees is limited and site conditions are particularly stressful. In these sites, tree-ring widths reflect a high degree of year-to-year moisture variability (Fritts 1976). While reconstructions of precipitation rely on a direct relationship between moisture and tree
growth, the relationship between tree growth and streamflow is less direct (Meko, Stockton, and Boggess 1995). In the case of the upper Colorado River Basin, water year streamflow and annual ring widths are both the result of the cumulative influence of hydroclimate conditions over the course of the water year. In both cases, cool season precipitation is the most important factor, leading to the snowpack that runs off into the river while conditioning spring soil moisture that is critical for tree growth (Woodhouse and Pederson 2018). Because of this relationship, trees most useful for streamflow reconstruction are not found in the floodplain, but instead are growing on uplands in the same “climate-shed” that produces the runoff for annual flow.

In the Colorado River Basin region, the low- to mid-elevation conifers (pinyon pine, ponderosa pine, and Douglas fir) are the species most sensitive to hydroclimate (Schulman 1956) and are targeted for collection. Once a site with the appropriate characteristics, tree species, and evidence of long-lived trees is located, approximately 20 living trees are sampled with an increment borer. Cross sections from dead trees, which can be preserved on the landscape for hundreds of years, may be cut with a chainsaw.

Back at the laboratory, each sample is dated to the exact calendar year using a pattern-matching technique called crossdating (Fritts 1976), which also enables wood from dead trees to be dated if it overlaps in time with the living trees. Once all samples are dated, they are measured using a sliding-stage micrometer to the precision of 0.001 mm. The time series of measurements typically show a declining trend over time in ring-width due to age and tree geometry, so the series are detrended to remove this effect, which is unrelated, for the most part, to climate (Cook and Kairiūkštis 1990). Two different “flavors” of detrended series are generated: one in which the low-order persistence in growth that is largely attributable to tree biology (year-to-year carbohydrate storage) is removed, resulting in so-called “residual” chronologies; and one in which that persistence is retained, resulting in “standard” chronologies. Measurements from all samples at a site are robustly averaged into a site tree-ring chronology, or time series, which is the basic unit used in the reconstruction process (Woodhouse et al. 2016).

Reconstructions of climate are developed by calibrating the annual tree-ring chronologies with a record of observed climate or hydrology over a common period of years. The calibration process usually employs some type of multiple linear regression, with tree-ring chronologies as the predictors and the observed climate or streamflow record as the predictand. There are many statistical approaches that may be taken for model calibration, but the two most common approaches are stepwise regression using individual chronologies as predictors, and principal
components regression, which reduces a set of chronologies to a smaller set of time series uncorrelated with each other that expresses the underlying principal modes of tree-growth variability, which are then used as the predictors.

Model validation is a key step in the reconstruction process. Validation involves withholding some subset of data, refitting the model on the remaining data, and assessing the model fit to the withheld data. This can be accomplished through cross-validation in which values from one or more years are iteratively removed and replaced until a complete validation time series has been generated (Michaelsen 1987; Woodhouse and Pederson 2018). Alternatively, a split-sample validation approach is used in which a portion of the calibration time series (typically at least 20 years) not included in the model calibration is used solely for model validation (Fritts, Guiot, and Gordon 1990).

The skill of the calibration model in estimating the observed values is assessed with statistics that include the explained variance ($R^2$) and standard error (SE). These statistics are compared to those generated from the validation data and include the reduction-of-error (RE) statistic (Fritts, Guiot, and Gordon 1990), which measures the ability of the reconstruction model to outperform a null model (e.g., the mean of the observed streamflows during the calibration period) and yields the root mean squared error (RMSE) of the validation data. Other visual and statistical comparisons are often performed as well.

10.2 Upper Colorado River Basin flow reconstructions

History of Upper Basin streamflow reconstructions

Edmund Schulman, one of the pioneers of tree-ring science, was the first to investigate the use of moisture-sensitive conifer tree rings to document past precipitation and streamflow in the Colorado River Basin (Figure 10.1). While Schulman’s work in the 1940s was based on relatively few tree-ring samples and predated the availability of computer-aided statistical modeling, his proxy record of streamflow captured the main features of later reconstructions that used far more tree-ring data and modern statistical calibration approaches (Schulman 1945). Schulman’s work included a report to the Los Angeles Department of Power and Light (“A Tree-Ring History of the Runoff of the Colorado River 1366–1941”), which indicates the interest of water-management agencies in tree-ring paleohydrology from its earliest days.
The first modern calibrated streamflow reconstructions for the Colorado River were developed by Stockton and Jacoby (1976), building on the preliminary work of Stockton (1975). Stockton and Jacoby developed multiple reconstruction models using two subsets of tree-ring chronologies and several different naturalized flow records for model calibration. Their final, published, Lees Ferry reconstruction was an average of the two models they deemed most reliable and extended from 1520–1961, with a long-term mean flow of 13.4 maf, explaining 87% of the variance in the 1914–1961 observed flow record (Stockton and Jacoby 1976).

Two additional Lees Ferry reconstructions were generated in the 1980s and 1990s based on the same or similar sets of tree-ring chronologies as Stockton and Jacoby, with models that used different types of multiple linear regression (Table 10.1): Michaelsen et al. (1990), in research undertaken for the California Department of Water Resources, and Hidalgo et al. (2000). The Hidalgo et al. long-term reconstructed mean flow of 13.0 maf is lower than any other reconstruction, likely as a result of their particular methodology, as discussed below.
Table 10.1  
Summary of statistical characteristics of published Colorado River at Lees Ferry reconstructions, updating Table U-6 in Reclamation (2007)

<table>
<thead>
<tr>
<th>Reconstruction</th>
<th>Calibration years</th>
<th>Source of Observed Natural Flow Data</th>
<th>Chronology Type</th>
<th>Regression approach</th>
<th>Variance explained ($R^2$)</th>
<th>Reconstruction years</th>
<th>1568–1961 mean (maf)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Stockton and Jacoby (1976)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>c. 1914–1961</td>
<td>UCRSFIG, 1971</td>
<td>standard</td>
<td>Regression approach</td>
<td>&quot;</td>
<td>0.87</td>
<td>1511–1961</td>
<td>13.0</td>
</tr>
<tr>
<td>Average of b and c</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>1520–1961</td>
<td>13.4</td>
</tr>
<tr>
<td>Michaelsen et al. (1990)</td>
<td>1906–1962</td>
<td>Simulated flows</td>
<td>residual</td>
<td>Best subsets</td>
<td>0.83</td>
<td>1568–1962</td>
<td>13.8</td>
</tr>
<tr>
<td>Hidalgo et al. (2000)</td>
<td>1914–1962</td>
<td>USBR (see ref)</td>
<td>residual</td>
<td>Alternative PCA with lagged predictors</td>
<td>0.82</td>
<td>1493–1962</td>
<td>13.0</td>
</tr>
<tr>
<td>(Lees–A)</td>
<td>1906–1995</td>
<td>USBR</td>
<td>residual</td>
<td>Stepwise</td>
<td>0.81</td>
<td>1490–1997</td>
<td>14.7</td>
</tr>
<tr>
<td>(Lees–B)</td>
<td>1906–1995</td>
<td>&quot;</td>
<td>standard</td>
<td>Stepwise</td>
<td>0.84</td>
<td>1490–1997</td>
<td>14.5</td>
</tr>
<tr>
<td>(Lees–C)</td>
<td>1906–1995</td>
<td>&quot;</td>
<td>residual</td>
<td>PCA</td>
<td>0.72</td>
<td>1490–1997</td>
<td>14.6</td>
</tr>
<tr>
<td>(Lees–D)</td>
<td>1906–1995</td>
<td>&quot;</td>
<td>standard</td>
<td>PCA</td>
<td>0.77</td>
<td>1490–1997</td>
<td>14.1</td>
</tr>
<tr>
<td>(most skillful)</td>
<td>1906–2015</td>
<td>USBR</td>
<td>standard</td>
<td>Interpolation from regression scatterplot, nested models</td>
<td>0.81</td>
<td>1416–2015</td>
<td>14.2</td>
</tr>
<tr>
<td>(longest)</td>
<td>1906–2014</td>
<td>USBR</td>
<td>standard</td>
<td>Same as above but no nesting</td>
<td>0.58</td>
<td>1116–2014</td>
<td>14.2</td>
</tr>
<tr>
<td>Gangopadhyay et al. (2009)</td>
<td>1922–1997</td>
<td>USBR</td>
<td>standard</td>
<td>K-Nearest Neighbor (K-NN)</td>
<td>0.76</td>
<td>1400–1905</td>
<td>³</td>
</tr>
<tr>
<td>Gangopadhyay et al. (2015)*</td>
<td>1910–1997</td>
<td>Simulated flows</td>
<td>standard</td>
<td>K-Nearest Neighbor (K-NN)</td>
<td>r = 0.63 (med)</td>
<td>1404–1905</td>
<td>³</td>
</tr>
</tbody>
</table>
Reconstruction | Calibration years | Source of Observed Natural Flow Data | Chronology Type | Regression approach | Variance explained ($R^2$) | Reconstruction years | 1568–1961 mean (maf)
---|---|---|---|---|---|---|---
Bracken et al. (2016)† | 1952–1997 | USBR residual | Nonhomogeneous Hidden Markov Chains (NHMC) | r = 0.91 | 1473–1906 | ²

*Includes additional reconstructions for 5 tributary gages
†Includes additional reconstructions for 19 main stem and tributary gages
‡The non-parametric models do not produce reconstructed flows for the post-1905 period, so comparisons over this full period are not possible

In the late 1990s and early 2000s, major efforts were undertaken to update and expand the tree-ring chronologies collected in the upper Colorado River Basin and adjacent areas. These new chronologies enabled the next generation of Colorado River reconstructions, which took advantage of the longer calibration period. Because the calibration period was extended to include an additional 33 to 53 years (the latter nearly doubling the calibration period of pre-2006 reconstructions), these reconstructions are considered more robust. This additional credibility is due to both the extended length of the calibration period and the broader range of variability for model calibration. The first of these new chronologies expanded the Lees Ferry streamflow reconstruction start and end dates to 1490–1997/1998 (Woodhouse, Gray, and Meko 2006). Under that effort, four different reconstruction models were developed to test the sensitivity of reconstruction results to 1) autocorrelation in the tree-ring data and 2) the multiple linear regression approach used.

On the heels of that work, Meko et al. (2007) developed a subset of tree-ring chronologies that incorporated remnant material from dead trees to extend the tree-ring records back even further in time, along with updated chronologies, to generate a reconstruction of streamflow from 762–2005. This extended reconstruction revealed a much larger range of variability, including a much longer period of sustained drought in the 12th century, than had been documented in the shorter reconstructions. This reconstruction was largely based on the same set of chronologies as used in Woodhouse et al. (2006) back to the 1400s: To deploy the largest set of available chronologies back in time, Meko et al. (2007) used four nested sub-period reconstruction models. While the explained variance for the model that covers the longest sub-period (1365–2002) is very similar to explained variance in the models for Woodhouse et al. (2006), the model covering the earliest period, extending back to 762, is less skillful (Table 10.1).

Figure 10.2 shows the locations of streamflow reconstructions in the Colorado River Basin.
Figure 10.2
Locations for which naturalized annual streamflows have been reconstructed using tree-ring records, with the reconstruction data available from the TreeFlow website. The lengths of the reconstructions range from 385 years to 1244 years. Three different reconstructions of the Colorado River at Lees Ferry are available from TreeFlow; see the text for more information about these and other Lees Ferry reconstructions. (Source: TreeFlow; https://www.treeflow.info)
Most recently, the California Department of Water Resources funded Meko and Woodhouse to update a subset of the Upper Basin tree-ring chronologies in order to include the most recent drought years in the streamflow calibration series (Meko, Woodhouse, and Bigio 2017). Under that effort, two Lees Ferry reconstructions were generated: a shorter, more skillful reconstruction (1416–2015; $R^2 = 0.81$) and a longer but less skillful reconstruction (1116–2015; $R^2 = 0.58$).

A comparison of all of the Lees Ferry reconstructions described above is shown in Figure 10.3 for the years they have in common, 1568–1961. Reconstructions have been smoothed with a 20-year moving average (plotted on the last year) to facilitate visual comparison. In general, the reconstructions are very similar in their depictions of the timing of shifts between high and low flow periods. The period in which reconstructions are perhaps most different is the wet period in the early 1600s, with the Michaelsen et al. (1990) reconstruction showing flows barely above their long-term average, while the more recent reconstructions show the highest values (Meko et al. 2007; Meko, Woodhouse, and Bigio 2017; Woodhouse, Gray, and Meko 2006). This suggests the influence of the larger set of tree-ring chronologies in the Upper Basin starting with the 2006–07 reconstructions.

![Figure 10.3](https://treeflow.info)

**Figure 10.3**
Comparison of eight tree-ring reconstructions of the Colorado River at Lees Ferry, showing the similarities in the timing of decadal-scale dry and wet periods. The most recent reconstructions (published after 2005) are emphasized with darker colors due to their more robust tree-ring datasets and longer calibration periods than earlier reconstructions. All series are smoothed with a 20-year moving average and plotted on the last year of the 20-year period. (Data: Treeflow [https://treeflow.info](https://treeflow.info) and C. Woodhouse)
The Hidalgo et al. (2000) reconstruction clearly differs the most from the others, showing much lower flows during drought periods than the other reconstructions. That reconstruction used a set of tree-ring chronologies similar to Stockton and Jacoby, but with a different PCA regression approach that apparently enhances the year-to-year persistence of flow anomalies, and thus the magnitudes of extended low-flow periods. An independent estimate of gaged flows during the late 1800s drought suggests that the Hidalgo et al. reconstructed flows during that period—and by extension, previous drought periods—are implausibly low. In the 1920s, a USGS hydrologist used observed stage height of the Colorado at Yuma to estimate annual flows at Yuma back to 1878; converting these to natural flows at Lees Ferry gives an average of 13.5 maf for the period 1886-1905 (Kuhn and Fleck 2019). The Hidalgo et al. reconstruction indicates only 10.4 maf for this same period, while the other seven reconstructions are in the range of 12.1–13.4 maf.

In addition to these regression-based (i.e., parametric) reconstructions of the Colorado River at Lees Ferry, reconstructions have been generated using non-parametric statistical approaches. The non-parametric approaches do not assume that the data are normally distributed, and can produce ensembles of reconstructed flow values for each year, expressing the uncertainty in the reconstruction. These non-parametric reconstructions have generally used the same set of tree-ring chronologies developed for Woodhouse et al. (2006) and Meko et al. (2007), along with a few updated chronologies. Gangopadhyay et al. (2009) employed K-nearest neighbor (K-NN) techniques to develop an ensemble of Lees Ferry annual streamflow traces. Bracken et al. (2016) used a hierarchical Bayesian nonhomogeneous hidden Markov model (NHMM) to develop reconstructions for a network of 20 Upper Basin gages, including Lees Ferry. Both sets of reconstructions extend back to the 15th century, with mean explained variance of $R^2 = 0.76$ (Gangopadhyay et al. 2009) and $R^2 = 0.83$ (Bracken, Rajagopalan, and Woodhouse 2016), respectively, indicating overall skill similar to regression-based reconstructions.

The main strength of these approaches over linear regression is their explicit representation of uncertainty with more realistic confidence intervals, and in the case of Bayesian NHMM, the replication of observed spatial relationships among tributary gages. The resulting reconstructions themselves are similar in skill to those produced by regression approaches, and also show similar magnitudes for the extended dry and wet periods, clearly demonstrating the robustness of the overall hydroclimatic signal that emerges from the current set of tree-ring chronologies in this region (Table 10.1).

Most recently, Gangopadhyay et al. (2015) used a water balance model and the set of chronologies that had been used in Gangopadhyay et al. (2009) in
a K-NN approach to generate a suite of hydroclimatic reconstructions, including the Colorado River at Lees Ferry, back to 1404. In that case, the median correlation between the water year streamflow reconstructions (1906–1997) and the observed flow record was $r = 0.63$.

In addition to these reconstructions of the Colorado River at Lees Ferry, water year streamflow has been reconstructed for 30 other main stem and tributary gages throughout the Upper Basin, as well as 4 tributary gages in the Lower Basin, all in the Gila River basin. These reconstructions are listed in the TreeFlow web resource (CLIMAS and WWA n.d.), with links to the data and metadata.

**Comparison of recent Lees Ferry reconstructions**

The Lees Ferry streamflow reconstructions generated since 2006 (Woodhouse, Gray, and Meko 2006; Meko et al. 2007; Meko, Woodhouse, and Bigio 2017) have used the same or very similar sets of tree-ring chronologies as potential predictors of streamflow. Consequently, these regression-based reconstructions are quite similar (average correlation between reconstructions over common years: $r = 0.88$, ranging from $r = 0.76$ to $r = 0.96$) but with some key differences that highlight the impact of choices made when reconstruction models were developed. These differences are mostly due to treatment of the autocorrelation that is found in the ‘raw’ tree-ring data and type of multiple linear regression modeling used.

Most obvious are the differences in explained variance (Table 10.1). The reconstructions, or portions of reconstructions, that extend farthest back in time have the lowest skill, as they are based on a much-reduced subset of the tree-ring chronologies—for example, the Meko et al. (2007) model that starts in 762, and the Meko et al. (2017) longest reconstruction. Putting these two aside, the explained variance of the other reconstructions ranges from $R^2 = 0.77$ to $R^2 = 0.84$.

Since the reconstructions listed in Table 10.1 used different calibration periods and different natural flow records for calibration, a more uniform comparison of the reconstructions can be made based on their correlations with the latest version of the Lees Ferry estimated natural flows (as of September 2018) over a common interval of time (1906–1997). In this comparison, the reconstructions with the highest correlations with flow are non-PCA regression reconstructions from Woodhouse et al. (2006) (Lees B, standard chronologies, $r = 0.916$) and Meko et al. (2017) (shorter more skillful version, $r = 0.914$), followed by the Lees A (residual chronologies, $r = 0.895$). The two that are most skillful are generated from standard chronologies, i.e., those with biological persistence retained, so that the series contain statistically significant lag-1 autocorrelations.
Going beyond the strength of the relationships between reconstructed and estimated natural flows, an examination of basic statistical characteristics such as the minimum, maximum, and range coincides with what might be expected, given differences in explained variance. In other cases, the results provide some insights into modeling choices. Perhaps the most revealing comparison is with the lag-1 autocorrelation values, i.e., year-to-year persistence. In the observed flow record, this value is $r = 0.235$ (significant at $p = 0.02$). The reconstructions based on residual chronologies, in which biological persistence was removed (Lees A and Lees C), as expected show autocorrelation values over the calibration period of $r \approx 0$. The two Meko et al. (2017) reconstructions have somewhat higher persistence ($r = 0.338$ and $r = 0.379$) than the observed natural flows, while Lees B ($r = 0.221$) and Lees 2007 ($r = 0.243$) appear to be the closest match to the persistence in the observed natural flows. Higher autocorrelation values will result in longer periods of drought being seen in the reconstructed flows. For example, the Meko et al. (2017) most-skillful reconstruction contains two 10-year, one 11-year, and one-15 year drought over the years 1416–2005, while the longest drought shown in Lees 2007 during this same period lasted only 8 years. (Drought is defined here as consecutive years below the observed average.)

There is no perfect reconstruction and trade-offs are unavoidable, the most obvious being between skill and length. But this comparison does suggest that the use of standard chronologies preserves important autocorrelation in the system, though more work is needed to determine what modeling choices beyond the type of chronology may better replicate the autocorrelation in the observed hydrology. Given this, any of the following recent reconstructions of Lees Ferry flow would be appropriate for water supply analysis and as inputs to system modeling; the fact that they show differences between them is reflective of the uncertainties inherent in any one reconstruction, as outlined in the next section.

- Lees B (Connie A. Woodhouse, Gray, and Meko 2006)
- Lees 2007 (Meko et al. 2007)
- Lees 2017, either model (Meko, Woodhouse, and Bigio 2017)
- Gangopadhyay et al. K-NN (Gangopadhyay et al. 2009)
- Bracken et al. NHMM (Bracken, Rajagopalan, and Woodhouse 2016)

Of these reconstructions, Lees 2007 has seen the most use in recent water-supply analyses for the basin, including those supporting the 2007 Interim Guidelines (Appendix N; Reclamation 2007b) and in the Basin Study (Reclamation 2012b). Lees-B was used in the initial analyses performed for the Draft EIS for the 2007 Interim Guidelines.
SPOTLIGHT

Megadroughts: Past occurrences and future risk

The term *megadrought* was first used by Woodhouse and Overpeck (1998) to refer to droughts, as documented by paleoclimatic data, that lasted longer than any that occurred in the period of instrumental data across the central and western U.S. The term was then highlighted in Stahle et al.’s paper, “Tree-Ring Data Document 16th Century Megadrought of North America” (Stahle et al. 2000), and has been widely used since.

A megadrought is most often defined as a drought over a given area or for a spatial extent that is as severe as, but longer than, any in the 20th century (e.g., Cook 2004; Ault and St. George 2018). The definition may include a more specific interval, such as 20–40 years (Herweijer et al. 2007), longer than 35 years (Ault and St. George 2018), or include any droughts that exceed both the duration and severity of 20th century droughts (Stahle et al. 2007). While many droughts during the pre-instrumental (pre-1900) period have been identified as megadroughts, the most well-known are those of the medieval period (~850–1300), which extended across western North America, including the Colorado River Basin (Cook 2004; Meko et al. 2007). In the Upper Basin, the most notable megadrought occurred during the mid-1100s, with 13 consecutive years of below-average reconstructed flow at Lees Ferry, and the driest 25-year period (1130–1154), averaging less than 84% of the observed period average flow for 1906–2004 (Meko et al. 2007). Figure 10.4 shows the mid-1100s megadrought and three others that occurred between 800 and 1600.

Tropical Pacific sea surface temperature (SST) variability, and specifically, persistent cool anomalies, similar to La Niña events, has been suggested as the primary causal mechanism for the medieval-era megadroughts, with a possible role for SSTs in the Atlantic (Seager et al. 2008). Studies using GCMs that show megadrought behavior in pre-20th century simulations strongly suggest that internal climate variability alone has been responsible for these droughts (Coats et al. 2015). The medieval period of more frequent and persistent droughts does not appear to have been accompanied by similarly persistently cool tropical Pacific SSTs, suggesting a mean shift did not occur over this period, and that other modes of climate variability also played a role (Coats et al. 2016).

What we know about the causes of megadroughts suggests that events like the persistent droughts of the medieval period could occur in the future due to natural climate variability alone. Recurrences of such droughts would produce even lower flows than shown in the reconstructions due to the additional impact of warmer conditions (Woodhouse et al. 2010). For example, Udall and Overpeck (2017) concluded that a recurrence of the lowest 25-year period in the Lees 2007 Colorado River flow reconstruction, which had flows of 84% of average, would, in a warmer future, have flows of 78% of average under a 1°C (1.8°F) warming and 65% of average under a 3°C (5.4°F) warming, assuming a mid-range temperature sensitivity of basin runoff.
A number of studies have employed both paleoclimatic reconstructions of drought and output from multiple global climate models to estimate the risk of drought across the southwestern U.S., including the basin, over the next century. Cook et al. (2015) found that drought risk across the U.S. Southwest and Central Plains is likely to surpass even the driest centuries of the medieval period, under both moderate-emissions (RCP4.5) and high-emissions scenarios (RCP8.5). In the Southwest, the risk of decadal-scale megadrought is estimated to be at least 80%, the risk of a 35-year megadrought from 20-50%, and the risk of a 50-year megadrought under the highest emissions scenario is 5-10% (Ault et al. 2014). The importance of warming temperatures in this region is highlighted by Ault et al. (2016), who found that megadrought risk increased to above 90% by the end of the 21st century, even without changes in precipitation. This importance of warming temperatures with regard to reduction in flow was underscored by the findings of Udall and Overpeck (2017) for the Colorado River.

![Figure 10.4](image)

**Figure 10.4**
Comparison of the reconstructed annual flows, with a 20-year running average, for the Colorado River at Lees Ferry from Meko et al. (2007) (‘Lees 2007’) and Meko et al. (2017) (‘Lees Long 2017’; long version). Four megadroughts are highlighted in yellow, the first three of which occurred during the medieval period: 1) one in the 9th century, 2) one in the 12th century, 3) one in the late 13th and early 14th century, and 4) one in the late 16th century. Other paleoclimate reconstructions indicate that the impacts of these four megadroughts extended throughout much of western North America.
10.3 Sources of uncertainty in tree-ring reconstructions

Because tree rings are imperfect proxies for streamflow, there are inevitable uncertainties in the reconstructions. Additional uncertainties arise from the choices made during the handling of the tree-ring data and the reconstruction model. A more detailed overview of the sources of reconstruction uncertainty can be found in Meko and Woodhouse (2011). The factors that lead to differences and uncertainty include:

- Noise in the trees’ recording of hydroclimatic conditions (signal)
- The selection of the tree-ring chronologies to use in the pool of candidate predictors
- The processing of those chronologies (detrending method; residual vs. standard chronology)
- The selection of the naturalized streamflow record used in the calibration
- The length of the calibration period
- The choice of statistical model used for calibration
- The choice of calibration/validation scheme

Metrics of error such as RMSE quantify the uncertainty for an individual reconstruction related to the imperfect calibration fit between the modeled flow and the observed flow, and allow one to construct confidence intervals around the reconstruction. But RMSE and resulting confidence intervals do not capture the uncertainties related to the data handling and modeling choices above. The overall effect of these uncertainties is better illustrated by the differences between the various Lees Ferry reconstructions (Table 10.1, Figure 10.3).

While the Colorado River streamflow reconstructions have some of the most robust calibration/verification statistics of any tree-ring reconstructions of hydroclimate, 20% or more of the variance in the gage record remains unexplained. Linear regression modeling, used for most of the reconstructions in Table 10.1, tends to compress the range of the input data, so that extreme low-flow values are typically overestimated by the model, and extreme high-flow values are typically underestimated. Consequently, the reconstructed values for drought years can be interpreted as conservative estimates of actual streamflows in most cases.

10.4 Value and application of paleohydrology in water supply analyses

Reconstructions of Colorado River streamflow extend the gaged record up to 1200 years into the past and document a broader range of hydrologic variability and extremes than are contained in the relatively short observed
records. They indicate, for example, that drought events far more persistent than any observed over the instrumental period have occurred under natural climate variability alone; that is, without significant human influence on the climate (Meko et al. 2007). The reconstructions also clearly document that the hydroclimate of the basin has been non-stationary; the mean and variability are not constant from one century to the next. While climate change will be a major driver of non-stationarity in hydrology in the future (Milly et al. 2008), the reconstructions provide abundant evidence of time periods with statistical characteristics quite different from those of the 20th century.

One example is the 12th century, which was characterized by multiple runs of below-average flow for the Colorado River at Lees Ferry, including a nearly 60-year period (1110–1170) with only 12 years of above-average flow (Meko et al. 2007). The reconstructed flows for the 12th century had lower mean flow, a smaller range of flow values, and a much higher persistence (r = 0.55 vs. r = 0.26; see Chapter 2) compared to the reconstructed flows for the 20th century. This type of non-stationarity is also seen in wavelet spectra that show changes in the multidecadal variability in reconstructed streamflow over the past six centuries (Woodhouse, Gray, and Meko 2006).

Because of their multi-century to millennial length, reconstructions of streamflow also document variability at time scales longer than what can be discerned from the instrumental record. Time-series analysis reveals a multidecadal peak signal in Colorado River flow at about 50–60 years, suggesting a phasing of wet and dry periods at this interval, although the strength of this phasing varies over time, and it is not clearly associated with a defined climate oscillation such as the AMO or PDO (Woodhouse, Gray, and Meko 2006; Meko, Woodhouse, and Bigio 2017). Such expressions of multi-decadal variability cannot be detected using observed records, given their limited length.

Also due to their extended length, reconstructions contain extremes that may not be represented in the shorter instrumental period, and allow an assessment of events experienced in the observed record in a centuries-long context. Upper Basin reconstructions have documented the unusualness of the high-flow period of the early 20th century as well as droughts more severe than any that occurred in the 20th century. While the ongoing 21st century drought may eventually match the persistence of the longest droughts of the past eight centuries, the medieval period (~850–1300) stands out as an interval of frequent persistent droughts, with multiple runs of eight to ten years of consecutively below average flows. Persistent drought in the 12th century is especially notable, as mentioned above. Statistical analysis suggests that the worst 25-year period of drought in the 12th century—with a mean flow of 84% of the 1906–2004 observed average or less (Meko et al. 2007)—has a probability of occurring once every
The information from the reconstructions of past flow has been useful for providing context for the assessment of observed and GCM-based hydrology (Reclamation 2007c; 2012e). While the record of the past is unlikely to be replicated in the future, the paleohydrology records contain important information about the range of natural variability that has occurred in the past, and thus could occur again. This perspective is especially critical since GCMs do not appear to simulate the full magnitude of decadal to century-scale variability as reflected in long proxy records, including the Colorado River reconstructions (Ault et al. 2013; Woodhouse, Gray, and Meko 2006). The GCMS also appear to underestimate the risk of persistent severe droughts, such as those of the 12th century (Ault et al. 2014). The reconstructions of past streamflow can be particularly valuable in cases where climate models are not very informative or well accepted by practitioners.

Applications in Reclamation-led planning studies
Reclamation first used tree-ring based reconstructions of Colorado River flow in analyses to support the 2007 Interim Guidelines; the analyses based on reconstructed flows were included in Appendix N of the Final EIS (Reclamation 2007b). The reconstructed flow values were used to test the sensitivity of the modeled system in Reclamation’s Colorado River Simulation System (CRSS) to a broader range of hydrologic conditions than allowed by the observed hydrology alone. CRSS runs on monthly time steps and requires input for 29 inflow points in the basin (see Chapter 3), while the tree-ring reconstruction that was chosen (Lees 2007), like all such reconstructions, has annual values for a single river location (Lees Ferry). This is a common challenge in using tree-ring reconstructions in water resources planning: system models usually require spatial and temporal inputs at finer resolutions than provided by the annual flow reconstruction. Thus, spatial and temporal disaggregation was a key part of the two methods used by Reclamation to develop CRSS-ingestible hydrologic traces from the (Meko et al. 2007) reconstruction.

The first method, called Direct Paleo or Paleo Resampled, uses the sequences of flow magnitudes directly from Lees 2007. A K-NN approach is used to first disaggregate the annual reconstruction series for Lees Ferry into monthly data by effectively replacing each reconstructed flow value at Lees Ferry (e.g., 1258) with a year and associated monthly values from the observed natural flow record (e.g., 1954) that is sampled from a small set of
“nearest neighbors” to that reconstructed flow value. Then the resulting simulated Lees Ferry monthly flows are disaggregated spatially to all 20 inflow points in the Upper Basin, with the monthly flows at the 9 inflow points in the Lower Basin being taken from the analog year’s observed values (Prairie et al. 2006; 2007). These disaggregated flows (1244 years of monthly flows at 29 sites) are then resampled using the Index Sequential Method (ISM; Chapter 9), generating 1244 unique traces of 53 years in length. Since ISM sequentially block- bootstraps the streamflow data, the generated traces at Lees Ferry consist of the same annual flow magnitudes and sequences as seen in the Lees 2007 reconstruction, with the exception of the 4% of the traces that “wrap” the beginning around to the end of the reconstruction.

The second method, Non-Parametric Paleo Conditioning, reflects the rich variety of flow sequences in the reconstructed flow record (Lees 2007) but constrains the annual values to the range of annual flow magnitudes seen in the observed flow record. The state-transition probabilities—the likelihood that a high-flow year will be followed by a low-flow year, and vice-versa—are extracted from the streamflow reconstruction and then are used to conditionally resample the Lees Ferry observed flows, repeatedly, generating 125 unique traces of 53 years (Reclamation 2007b; 2012e; Prairie et al. 2008; Rajagopalan et al. 2009). The resulting paleo-conditioned Lees Ferry flows are then spatially and temporally disaggregated to monthly inflows at all 29 CRSS inflow points as described above.

Both sets of paleohydrology-informed flow traces, when run through CRSS, showed a higher risk of undesirable system outcomes by the end of the planning period than the flow traces using the observed hydrology (Reclamation 2007b). For example, under the Direct Paleo traces that included the severe and sustained drought in the 1100s, the levels of Lake Powell and Lake Mead declined to levels below their hydropower pools, and in the case of Lake Mead, to dead pool (Figure 10.5). This finding illustrates the value of tree-ring paleohydrology in developing water-supply scenarios that are more stressful than the observed hydrology, and are physically plausible because they are anchored in past hydroclimatic behavior.

In the Basin Study, the same two sets of paleohydrology-informed flow traces were again used as water supply scenarios in CRSS, along with multiple demand and management scenarios, to evaluate system vulnerability and resilience (Reclamation 2012e). A key difference between the Interim Guidelines EIS analyses in 2007 and the Basin Study analyses in 2012 was that the paleohydrologic traces were integral to the main analyses and findings of the Basin Study, rather than being offered as supplementary material in an appendix. Another difference was that, in the Basin Study, the system outcomes under the paleohydrologic traces were compared to
outcomes under traces informed by global climate models (Chapter 11), as well as by the observed hydrology.

Figure 10.5
Example of the use of paleohydrology-informed flow traces to evaluate Colorado River system vulnerability under plausible hydroclimate futures. Here, Lake Powell elevations for a 53-year period are modeled using synthetic “Paleo Conditioned” flow traces run through the CRSS model under two management scenarios: the No-action Alternative (NA), and the Preferred Alternative (PA), from the 2007 Interim Guidelines Final EIS. The flow traces are based on wet-dry transition information from the Meko et al. (2007) tree-ring reconstruction of Lees Ferry. The drought that occurs in these two scenarios from roughly 2020–2030 does not correspond to a particular reconstructed paleodrought, but is consistent with the statistical characteristics of paleodroughts. (Source: Reclamation 2007b).

Other applications by basin water agencies
Tree-ring reconstructions of streamflow for Lees Ferry and other gages in the basin have been used by several water agencies in diverse applications over the last few decades. These include, most notably, the California Department of Water Resources, Denver Water, and the Salt River Project, who have all funded the development of new tree-ring chronologies,
including new field collections, in addition to new streamflow
reconstructions for gages critical to water supplies. Some of these
applications, as in the Reclamation analyses, have used reconstructed flows
as inputs to water system models to assess system response and sensitivity
to extreme events and sequences of flow years that are not represented in
the instrumental data records (Rice, Woodhouse, and Lukas 2009). Other
agencies have conducted analyses outside of system models to place recent
drought events in a long-term context, assess risk of recurrence, and
evaluate worst-case scenarios for planning (Woodhouse and Lukas 2006;
Meko and Woodhouse 2011; Meko, Woodhouse, and Morino 2012). The
reconstructions have also been used to provide a general awareness of the
range of hydroclimatic conditions possible, including the frequency and
duration of droughts, in communications with boards, elected officials,
customers, and the general public (Rice, Woodhouse, and Lukas 2009).

10.5 Tree-ring reconstructions of other hydroclimate variables

Besides annual streamflow, several other hydroclimate variables have been
reconstructed for the upper Colorado River Basin. The moisture-limited
tree-ring chronologies in and near the basin are largely sensitive to
precipitation that falls between the autumn prior to the growing season
and the early part of the growing season. The specific window of months to
which tree growth is most sensitive varies with species and to some extent,
site characteristics (Woodhouse and Pederson 2018). Consequently, it is
feasible to reconstruct seasonal moisture variables such as cool-season
precipitation and April 1 SWE, for specific regions or sub-basins, as well as
for the entire basin (Woodhouse 2003; Gray et al. 2004; MacDonald and
Tingstad 2007; Pederson et al. 2011; Woodhouse and Pederson 2018).

The network of existing tree-ring chronologies has also been used for:

- Reconstructing climate and climate-related indices that, like
  streamflow, reflect an integrative response to hydroclimate, such as
  annual soil moisture (Anderson, Tootle, and Grissino-Mayer 2012) and
  the summer Palmer Drought Severity Index (Cook et al. 2004, 2007,
  2010)

- Reconstructing a full suite of water-balance variables (e.g., potential
  evapotranspiration, actual evapotranspiration, SWE, soil moisture
  storage, and runoff), though with varying degrees of robustness
  (Gangopadhyay, McCabe, and Woodhouse 2015)

- Developing independent (with respect to chronologies) reconstructions
  of water-year streamflow and cool-season precipitation to estimate
  runoff efficiency in the Upper Basin (Woodhouse and Pederson 2018)
Tree-ring reconstructions have also been used to explore the variation in large-scale influences on basin climate and hydrology over past centuries, including El Niño–Southern Oscillation (ENSO; Chapter 2). With several reconstructions of ENSO variability available from tree rings and other proxy data (e.g., Braganza et al. 2009; Gergis et al. 2006), it is tempting to investigate long-term relationships between basin hydroclimate and ENSO. However, as described in Chapter 2, the ENSO influence on Upper Basin streamflow is generally weak. More problematically, there are large differences between the reconstructions of ENSO themselves, adding an additional layer of uncertainty to this type of analysis (Wilson et al. 2010). Similarly, a number of paleo-reconstructions of Pacific Decadal Oscillation (PDO) have been generated (Biondi, Gershunov, and Cayan 2001; D’Arrigo, Villalba, and Wiles 2001; Gedalof, Mantua, and Peterson 2002; MacDonald and Case 2005). While these reconstructions show a great deal of consistency during the post-1900 calibration period, they greatly diverge prior to the 20th century, suggesting that the PDO itself may be unstable over space and time (Wise 2015), or that the teleconnected influences on western North America climate are unstable.

### 10.6 Blending paleohydrology and climate change information

The record of past hydroclimatic variability will not be exactly replicated in the future because of the large random component of natural variability, as well as the unprecedented impacts of human activities on climate. While the modes and expressions of natural variability as documented in the reconstructions may be significantly altered by future human-caused climate forcing, there has been very little research to examine such potential changes. Thus, in the absence of evidence to the contrary, it is safer to assume that these modes and expressions of variability will continue. As far as we know, there is no reason that an event such as the severe and sustained drought of the mid-1100s could not occur in the future.

As noted above, the main value of the tree-ring reconstructions is in their broader and richer sequences of wet and dry years, compared to the instrumental record. This information can be combined with the most robust aspects of climate projections from GCMs (i.e., future warming) to develop plausible scenarios for future hydrology. There have been several past and ongoing efforts to blend paleohydrology and climate-change information.

Brekke et al. (2009) explored ways to represent information in both climate projections and paleoclimate data (in this case, runoff statistics) to inform water supply planning assumptions, using the Gunnison River as one of two
test cases. Gray and McCabe (2010) demonstrated an approach that used a water-balance model to blend long-term precipitation variability with warming temperatures to produce projections of streamflow and drought for the upper Yellowstone River in Montana. In the Colorado River Water Availability Study (CWCB 2012), projected temperature changes and precipitation changes from GCMs were used in a hydrologic model (VIC; Chapter 6) to alter historical flow values, which were then re-sequenced into synthetic flow traces using information from the Meko et al. (2007) Lees Ferry reconstruction and Reclamation’s “paleo-conditioning” method as described earlier. An ongoing project funded by the DOI Southwest Climate Adaptation Science Center includes the development of an approach that blends tree-ring reconstructed basin cool-season precipitation with warmer temperatures consistent with GCM projections. The approach uses synthetic temperature series elevated by 2° to 4°C, or incorporating a warming trend, to generate streamflow using the McCabe and Wolock (2011) water-balance model.

### 10.7 Challenges and opportunities

Tree-ring paleohydrology is a relatively mature science, with a 75-year history, and the recent reconstructions of Colorado River (Lees Ferry) streamflow collectively provide a very robust view of pre-1900 hydrologic variability from interannual to century time scales. There are unlikely to be significant future improvements in the already high skill of these reconstructions. But there is more work to be done to refine the application of the reconstructions in water-supply planning, including establishing a stronger conceptual and practical basis for merging the reconstructions with future projections of streamflow.

#### Challenge: Updating chronologies and reconstructions

At present, only seven tree-ring site chronologies in the Upper Basin extend beyond 2005, so current streamflow reconstructions do not have the benefit of full calibration against the early 21st century dry period. Additionally, Reclamation’s ongoing revisions of natural flow estimates (Chapter 5) may, cumulatively, substantially revise the target hydrology for tree-ring flow reconstructions.

#### Opportunities

- Develop new or updated tree-ring site chronologies that can be included in the calibration of any forthcoming streamflow reconstructions.
- Consider recalibration of, as well as assessment of the sensitivity of, the tree-ring flow reconstructions to the revised natural flows.
• Generate new, targeted reconstructions for the key water supply regions of the Upper Basin like the ongoing project funded by the USGS Southwest Climate Adaptation Science Center, in collaboration with basin water managers.

**Challenge: Blending paleo with climate projections**

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

**Opportunity**

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

**Challenge: Reconstructions of temperature**

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

**Opportunity**

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


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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.
distribut**ed**
In hydrologic modeling, a distributed model explicitly accounts for spatial variability by dividing basins into grid cells. Contrast with **lumped** model.

downscale**ng**
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.

evironmental 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 (gaged) record, typically using environmental proxies such as tree rings.

parameterized
Referring to a key variable or factor that is represented in a model by an estimated value (parameter) based on observations, rather than being explicitly modeled through physical equations.

parametric
A statistical method that assumes an underlying mathematical function, specified by a set of characteristics, or parameters (e.g., mean and standard deviation) for a sample of observations.

persistence
In hydrology, the tendency of high flows to follow high flows, and low flows to follow low flows. Hydrologic time series with persistence are autocorrelated.

phreatophytes
Plants with deep root systems that are dependent on water from the water table or adjacent soil moisture reserves.

pluvial
An extended period, typically 5 years or longer, of abnormally wet conditions; the opposite of drought.

principal components regression (PCR)
A statistical technique for analyzing and developing multiple regressions from data with multiple potential explanatory variables.

prior appropriation
“First in time, first in right.” The prevailing doctrine of water rights for the western United States; a legal system that determines water rights by the earliest date of diversion or storage for beneficial use.

probability density function (PDF)
A function, or curve, that defines the shape of a probability distribution for a continuous random variable.

projection
A long-term (typically 10-100 years) forecast of future hydroclimatic conditions that is contingent on specified other conditions occurring during the forecast period, typically a particular scenario of greenhouse gas emissions.

quantiles
Divisions of the range of observations of a variable into equal-sized groups.

r
Correlation coefficient. The strength and direction of a linear relationship between two variables.
\( R^2 \)
The proportion of variance in a dependent variable that's explained by the independent variables in a regression model.

**radiometer**
An instrument used to detect and measure the intensity of radiant energy, i.e., shortwave energy emitted from the sun and reflected by clouds, and longwave energy emitted from the earth’s surface.

**raster**
A digital image or computer mapping format consisting of rows of colored pixels.

**reanalysis**
An analysis of historical climate or hydrologic conditions that assimilates observed data into a modeling environment to produce consistent fields of variables over the entire period of analysis.

**reference evapotranspiration**
An estimate of the upper bound of evapotranspiration losses from irrigated croplands, and thereby the water need for irrigation.

**regression**
A statistical technique used for modeling the **linear relationship** between two or more variables, e.g., snowpack and seasonal streamflow.

**relative humidity (RH)**
The amount of moisture in the atmosphere relative to the amount that would be present if the air were saturated. RH is expressed in percent, and is a function of both moisture content and air temperature.

**remote sensing**
The science and techniques for obtaining information from sensors placed on satellites, aircraft, or other platforms distant from the object(s) being sensed.

**residual**
The difference between the observed value and the estimated value of the quantity of interest.

**resolution**
The level of detail in model output; the ability to distinguish two points in space (or time) as separate.

- **spatial resolution** - Resolution across space, i.e., the ability to separate small details in a spatial representation such as in an image or model.
- **temporal resolution** - Resolution in time, i.e., hourly, daily, monthly, or annual. Equivalent to time step.

**return flow**
The water diverted from a river or stream that returns to a water source and is available for consumptive use by others downstream.
runoff
Precipitation that flows toward streams on the surface of the ground or within the ground. Runoff as it is routed and measured within channels is streamflow.

runoff efficiency
The fraction of annual precipitation in a basin or other area that becomes runoff, i.e., not lost through evapotranspiration.

sensible heat flux
The flow of heat from the Earth’s surface to the atmosphere without phase changes in the water, or the energy directly absorbed/released by an object without a phase change occurring.

shortwave radiation
Incoming solar radiation consisting of visible, near-ultraviolet, and near-infrared spectra. The wavelength spectrum is between 0.2 and 3.0 micrometers.

skew
The degree of asymmetry in a given probability distribution from a Gaussian or normal (i.e., bell-shaped) distribution.

skill
The accuracy of the forecast relative to a baseline “naïve” forecast, such as the climatological average for that day. A forecast that performs better than the baseline forecast is said to have positive skill.

smoothing filter
A mathematical filter designed to enhance the signal-to-noise ratio in a dataset over certain frequencies. Common signal smoothing techniques include moving average and Gaussian algorithms.

snow water equivalent (SWE)
The depth, often expressed in inches, of liquid water contained within the snowpack that would theoretically result if you melted the snowpack instantaneously.

snow course
A linear site used from which manual measurements are taken periodically, to represent snowpack conditions for larger area. Courses are typically about 1,000’ long and are situated in areas protected from wind in order to get the most accurate snowpack measurements.

snow pillow
A device (e.g., at SNOTEL sites) that provides a value of the average water equivalent of snow that has accumulated on it; typically the pillow contains antifreeze and has a pressure sensor that measures the weight pressing down on the pillow.

stationarity
The condition in which the statistical properties of the sample data, including their probability distribution and related parameters, are stable over time.

statistically significant
Unlikely to occur by chance alone, as indicated by one of several statistical tests.
stepwise regression
The process of building a regression model from a set of values by entering and removing predictor variables in a step-by-step manner.

stochastic method
A statistical method in which randomness is considered and included in the model used to generate output; the same input may produce different outputs in successive model runs.

stratosphere
The region of the upper atmosphere extending from the top of the troposphere to the base of the mesosphere; it begins about 11–15 km above the surface in the mid-latitudes.

streamflow
Water flow within a river channel, typically expressed in cubic feet per second for flow rate, or in acre-feet for flow volume. Synonymous with discharge.

sublimation
When water (i.e., snow and ice) or another substance transitions from the solid phase to the vapor phase without going through the intermediate liquid phase; a major source of snowpack loss over the course of the season.

surface energy balance
The net balance of the exchange of energy between the Earth’s surface and the atmosphere.

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

temperature inversion
When temperature increases with height in a layer of the atmosphere, as opposed to the typical gradient of temperature decreasing with height.

tercile
Any of the two points that divide an ordered distribution into three parts, each containing a third of the population.

tilt
A shift in probabilities toward a certain outcome.

transpiration
Water discharged into the atmosphere from plant surfaces.

troposphere
The layer of the atmosphere from the Earth’s surface up to the tropopause (~11–15 km) below the stratosphere; characterized by decreasing temperature with height, vertical wind motion, water vapor content, and sensible weather (clouds, rain, etc.).
**undercatch**
When less precipitation is captured by a precipitation gage than actually falls; more likely to occur with snow, especially under windy conditions.

**unregulated flow**
Observed streamflow adjusted for some, but not all upstream activities, depending on the location and application.

**Upper Basin**
The parts of the Colorado River Basin in Colorado, Utah, Wyoming, Arizona, and New Mexico that are upstream of the Colorado River Compact point at Lee Ferry, Arizona.

**validation**
The process of comparing a model and its behavior and outputs to the real system, after calibration.

**variance**
An instance of difference in the data set. In regard to statistics, variance is the square of the standard deviation of a variable from its mean in the data set.

**wavelet analysis**
A method for determining the dominant frequencies constituting the overall time-varying signal in a dataset.
Acronyms & Abbreviations

24MS
24-Month Study Model

AET
actual evapotranspiration

AgriMET
Cooperative Agricultural Weather Network

AgWxNet
Agricultural Weather Network

AHPS
Advanced Hydrologic Prediction Service

ALEXI
Atmosphere-Land Exchange Inversion

AMJ
April-May-June

AMO
Atlantic Multidecadal Oscillation

ANN
artificial neural network

AOP
Annual Operating Plan

AR
atmospheric river

AR-1
first-order autoregression

ARKStorm
Atmospheric River 1,000-year Storm

ASCE
American Society of Civil Engineers

ASO
Airborne Snow Observatory

ASOS
Automated Surface Observing System

AVHRR
Advanced Very High-Resolution Radiometer

AWOS
Automated Weather Observing System

BCCA
Bias-Corrected Constructed Analog

BCSD
Bias-Corrected Spatial Disaggregation (downscaling method)

BCSD5
BCSD applied to CMIP5

BOR
United States Bureau of Reclamation

BREB
Bowen Ratio Energy Balance method

C3S
Copernicus Climate Change Service

CA
Constructed Analogues

CADSWES
Center for Advanced Decision Support for Water and Environmental Systems

CADWR
California Department of Water Resources

CanCM4i
Canadian Coupled Model, 4th generation (global climate model)

CBRFC
Colorado Basin River Forecast Center
<table>
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<tr>
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<th>Definition</th>
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<tr>
<td>CCA</td>
<td>Canonical Correlation Analysis</td>
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<tr>
<td>CCSM4</td>
<td>Community Climate System Model, version 4 (global climate model)</td>
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<td>CDEC</td>
<td>California Data Exchange Center</td>
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<tr>
<td>CDF</td>
<td>cumulative distribution function</td>
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<td>CESM</td>
<td>Community Earth System Model (global climate model)</td>
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<td>CFS</td>
<td>Climate/Coupled Forecast System</td>
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<td>CFSv2</td>
<td>Coupled Forecast System version 2 (NOAA climate forecast model)</td>
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<td>CHPS</td>
<td>Community Hydrologic Prediction System</td>
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<td>CIMIS</td>
<td>California Irrigation Management Information System</td>
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<td>CIR</td>
<td>crop irrigation requirement</td>
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<tr>
<td>CIRES</td>
<td>Cooperative Institute for Research in Environmental Sciences</td>
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<td>CLIMAS</td>
<td>Climate Assessment for the Southwest</td>
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<td>CLM</td>
<td>Community Land Model</td>
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<tr>
<td>CM2.1</td>
<td>Coupled Physical Model, version 2.1 (global climate model)</td>
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<tr>
<td>CMIP</td>
<td>Coupled Model Intercomparison Project (coordinated archive of global climate model output)</td>
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<td>CNRFC</td>
<td>California-Nevada River Forecast Center</td>
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<td>CoAgMET</td>
<td>Colorado Agricultural Meteorological Network</td>
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<td>CoCoRaHS</td>
<td>Community Collaborative Rain, Hail and Snow Network</td>
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<td>CODOS</td>
<td>Colorado Dust-on-Snow</td>
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<tr>
<td>CONUS</td>
<td>contiguous United States (the lower 48 states)</td>
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<td>COOP</td>
<td>Cooperative Observer Program</td>
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<td>CP</td>
<td>Central Pacific</td>
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<td>CPC</td>
<td>Climate Prediction Center</td>
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<td>CRB</td>
<td>Colorado River Basin</td>
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<td>CRBPP</td>
<td>Colorado River Basin Pilot Project</td>
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<td>CRPSS</td>
<td>Continuous Ranked Probability Skill Score</td>
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<td>CRSM</td>
<td>Colorado River Simulation Model</td>
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<td>CRSP</td>
<td>Colorado River Storage Project</td>
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<td>Acronym</td>
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<tr>
<td>CRSS</td>
<td>Colorado River Simulation System</td>
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<td>CRWAS</td>
<td>Colorado River Water Availability Study</td>
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<td>CSAS</td>
<td>Center for Snow and Avalanche Studies</td>
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<td>CTSM</td>
<td>Community Terrestrial Systems Model</td>
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<td>CU</td>
<td>consumptive use</td>
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<tr>
<td>CUL</td>
<td>consumptive uses and losses</td>
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<tr>
<td>CV</td>
<td>coefficient of variation</td>
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<td>CVP/SWP</td>
<td>Central Valley Project/State Water Project</td>
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<td>CWCB</td>
<td>Colorado Water Conservation Board</td>
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<td>CWEST</td>
<td>Center for Water, Earth Science and Technology</td>
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<td>DA</td>
<td>data assimilation</td>
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<tr>
<td>Daymet v.3</td>
<td>daily gridded surface meteorological data</td>
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<td>DCP</td>
<td>Drought Contingency Plan</td>
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<td>DEM</td>
<td>digital elevation model</td>
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<td>DEOS</td>
<td>Delaware Environmental Observing System</td>
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<td>DHSVM</td>
<td>Distributed Hydrology Soil Vegetation Model</td>
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<td>DJF</td>
<td>December-January-February</td>
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<td>DMDU</td>
<td>Decision Making Under Deep Uncertainty</td>
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<td>DMI</td>
<td>Data Management Interface</td>
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<td>DOD</td>
<td>Department of Defense</td>
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<td>DOE</td>
<td>Department of Energy</td>
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<tr>
<td>DOW</td>
<td>Doppler [radar] on Wheels</td>
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<td>DRI</td>
<td>Desert Research Institute</td>
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<td>DTR</td>
<td>diurnal temperature range</td>
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<td>EC</td>
<td>eddy-covariance method</td>
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<td>EC</td>
<td>Environment Canada</td>
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<td>ECCA</td>
<td>ensemble canonical correlation analysis</td>
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<td>ECMWF</td>
<td>European Centre for Medium-Range Weather Forecasts</td>
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<td>EDDI</td>
<td>Evaporative Demand Drought Index</td>
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<td>EFAS</td>
<td>European Flood Awareness System</td>
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<td>Acronym</td>
<td>Full Form</td>
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<td>EIS</td>
<td>Environmental Impact Statement</td>
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<td>En-GARD</td>
<td>Ensemble Generalized Analog Regression Downscaling</td>
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<td>ENSO</td>
<td>El Niño-Southern Oscillation</td>
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<td>EOF</td>
<td>empirical orthogonal function</td>
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<td>EP</td>
<td>Eastern Pacific</td>
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<td>ERC</td>
<td>energy release component</td>
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<td>ESI</td>
<td>Evaporative Stress Index</td>
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<td>ESM</td>
<td>coupled Earth system model</td>
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<td>ESP</td>
<td>ensemble streamflow prediction</td>
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<td>ESRL</td>
<td>Earth System Research Laboratory</td>
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<td>ET</td>
<td>evapotranspiration</td>
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<td>ET₀</td>
<td>Reference (crop) evapotranspiration</td>
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<td>EVI</td>
<td>Enhanced Vegetation Index</td>
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<td>FAA</td>
<td>Federal Aviation Administration</td>
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<td>FEWS</td>
<td>Famine Early Warning System</td>
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<td>FEWS</td>
<td>Flood Early Warning System</td>
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<td>FIRO</td>
<td>forecast-informed reservoir operations</td>
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<td>FLOR</td>
<td>Forecast-oriented Low Ocean Resolution (global climate model)</td>
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<td>FORTRAN</td>
<td>Formula Translation programming language</td>
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<td>FPS</td>
<td>Federal Priority Streamgages</td>
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<td>FROMUS</td>
<td>Forecast and Reservoir Operation Modeling Uncertainty Scoping</td>
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<tr>
<td>fSCA</td>
<td>fractional snow covered area</td>
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<td>FWS</td>
<td>U.S. Fish and Wildlife Service</td>
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<tr>
<td>GCM</td>
<td>global climate model, or general circulation model</td>
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<td>GEFS</td>
<td>Global Ensemble Forecast System</td>
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<td>GEM</td>
<td>Global Environmental Multiscale model</td>
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<td>GEOS</td>
<td>Goddard Earth Observing System (global climate model)</td>
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<td>GeoTiff</td>
<td>Georeferenced Tagged Image File Format</td>
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<tr>
<td>GFDL</td>
<td>Geophysical Fluid Dynamics Laboratory</td>
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<td>Acronyms and Abbreviations</td>
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<td>-----------------------------</td>
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</tr>
<tr>
<td><strong>GFS</strong></td>
<td>Global Forecast System model</td>
</tr>
<tr>
<td><strong>GHCN</strong></td>
<td>Global Historical Climatology Network</td>
</tr>
<tr>
<td><strong>GHCN-D</strong></td>
<td>Global Historical Climate Network-Daily</td>
</tr>
<tr>
<td><strong>GHG</strong></td>
<td>greenhouse gas</td>
</tr>
<tr>
<td><strong>GIS</strong></td>
<td>geographic information system</td>
</tr>
<tr>
<td><strong>GLOFAS</strong></td>
<td>Global Flood Awareness System</td>
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<tr>
<td><strong>GLOFFIS</strong></td>
<td>Global Flood Forecast Information System</td>
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<tr>
<td><strong>GOES</strong></td>
<td>Geostationary Operational Environmental Satellite</td>
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<tr>
<td><strong>GRACE</strong></td>
<td>Gravity Recovery and Climate Experiment</td>
</tr>
<tr>
<td><strong>GRIB</strong></td>
<td>gridded binary or general regularly-distributed information in binary form</td>
</tr>
<tr>
<td><strong>gridMET</strong></td>
<td>Gridded Surface Meteorological dataset</td>
</tr>
<tr>
<td><strong>GSSHAI</strong></td>
<td>Gridded Surface/Subsurface Hydrologic Analysis</td>
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<tr>
<td><strong>GW</strong></td>
<td>groundwater</td>
</tr>
<tr>
<td><strong>HCCD</strong></td>
<td>Historical Canadian Climate Data</td>
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<tr>
<td><strong>HCN</strong></td>
<td>Historical Climatology Network</td>
</tr>
<tr>
<td><strong>HDA</strong></td>
<td>hydrologic data assimilation</td>
</tr>
<tr>
<td><strong>HDSC</strong></td>
<td>Hydrometeorological Design Studies Center</td>
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<tr>
<td><strong>HEFS</strong></td>
<td>Hydrologic Ensemble Forecast Service</td>
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<tr>
<td><strong>HESP</strong></td>
<td>Hierarchical Ensemble Streamflow Prediction</td>
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<tr>
<td><strong>HL-RDHM</strong></td>
<td>Hydrologic Laboratory-Research Distributed Hydrologic Model</td>
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<tr>
<td><strong>HMT</strong></td>
<td>Hydromet Testbed</td>
</tr>
<tr>
<td><strong>HP</strong></td>
<td>hydrological processor</td>
</tr>
<tr>
<td><strong>HRRR</strong></td>
<td>High Resolution Rapid Refresh (weather model)</td>
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<tr>
<td><strong>HSS</strong></td>
<td>Heidke Skill Score</td>
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<tr>
<td><strong>HTESSEL</strong></td>
<td>Land-surface Hydrology Tiled ECMWF Scheme for Surface Exchanges over Land</td>
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<tr>
<td><strong>HUC</strong></td>
<td>Hydrologic Unit Code</td>
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<tr>
<td><strong>HUC4</strong></td>
<td>A 4-digit Hydrologic Unit Code, referring to large sub-basins (e.g., Gunnison River)</td>
</tr>
<tr>
<td><strong>HUC12</strong></td>
<td>A 12-digit Hydrologic Unit Code, referring to small watersheds</td>
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<td>Acronyms and Abbreviations</td>
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<td>-----------------------------</td>
<td></td>
</tr>
<tr>
<td><strong>ICAR</strong> Intermediate Complexity Atmospheric Research model</td>
<td></td>
</tr>
<tr>
<td><strong>ICS</strong> intentionally created surplus</td>
<td></td>
</tr>
<tr>
<td><strong>IDW</strong> inverse distance weighting</td>
<td></td>
</tr>
<tr>
<td><strong>IFS</strong> integrated forecast system</td>
<td></td>
</tr>
<tr>
<td><strong>IHC</strong> initial hydrologic conditions</td>
<td></td>
</tr>
<tr>
<td><strong>INSTAAR</strong> Institute of Arctic and Alpine Research</td>
<td></td>
</tr>
<tr>
<td><strong>IPCC</strong> Intergovernmental Panel on Climate Change</td>
<td></td>
</tr>
<tr>
<td><strong>IPO</strong> Interdecadal Pacific Oscillation</td>
<td></td>
</tr>
<tr>
<td><strong>IRI</strong> International Research Institute</td>
<td></td>
</tr>
<tr>
<td><strong>iRON</strong> Interactive Roaring Fork Observing Network</td>
<td></td>
</tr>
<tr>
<td><strong>ISM</strong> Index Sequential Method</td>
<td></td>
</tr>
<tr>
<td><strong>JFM</strong> January-February-March</td>
<td></td>
</tr>
<tr>
<td><strong>JJA</strong> June-July-August</td>
<td></td>
</tr>
<tr>
<td><strong>K-NN</strong> K-Nearest Neighbor</td>
<td></td>
</tr>
<tr>
<td><strong>Landsat</strong> Land Remote-Sensing Satellite (System)</td>
<td></td>
</tr>
<tr>
<td><strong>LAST</strong> Lane’s Applied Stochastic Techniques</td>
<td></td>
</tr>
<tr>
<td><strong>LERI</strong> Landscape Evaporative Response Index</td>
<td></td>
</tr>
<tr>
<td><strong>lidar</strong> light detection and ranging</td>
<td></td>
</tr>
<tr>
<td><strong>LOCA</strong> Localized Constructed Analog</td>
<td></td>
</tr>
<tr>
<td><strong>LSM</strong> land surface model</td>
<td></td>
</tr>
<tr>
<td><strong>M&amp;I</strong> municipal and industrial (water use category)</td>
<td></td>
</tr>
<tr>
<td><strong>MACA</strong> Multivariate Adaptive Constructed Analog</td>
<td></td>
</tr>
<tr>
<td><strong>maf</strong> million acre-feet</td>
<td></td>
</tr>
<tr>
<td><strong>MAM</strong> March-April-May</td>
<td></td>
</tr>
<tr>
<td><strong>MEFP</strong> Meteorological Ensemble Forecast Processor</td>
<td></td>
</tr>
<tr>
<td><strong>METRIC</strong> Mapping Evapotranspiration at high Resolution with Internalized Calibration</td>
<td></td>
</tr>
<tr>
<td><strong>MJO</strong> Madden-Julian Oscillation</td>
<td></td>
</tr>
<tr>
<td><strong>MMEFS</strong> Met-Model Ensemble Forecast System</td>
<td></td>
</tr>
<tr>
<td><strong>MOCOM</strong> Multi-Objective Complex evolution</td>
<td></td>
</tr>
<tr>
<td><strong>MODDRFS</strong> MODIS Dust Radiative Forcing in Snow</td>
<td></td>
</tr>
<tr>
<td>Acronym</td>
<td>Definition</td>
</tr>
<tr>
<td>-----------</td>
<td>---------------------------------------------------------------------------</td>
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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</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>
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<tr>
<td>NAM</td>
<td>North American Monsoon</td>
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<tr>
<td>NAO</td>
<td>North Atlantic Oscillation</td>
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<tr>
<td>NARCCAP</td>
<td>North American Regional Climate Change Assessment Program</td>
</tr>
<tr>
<td>NARR</td>
<td>North American Regional Reanalysis</td>
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<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>
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<tr>
<td>NCEI</td>
<td>National Centers for Environmental Information</td>
</tr>
<tr>
<td>NCEP</td>
<td>National Centers for Environmental Prediction</td>
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<tr>
<td>nClimDiv</td>
<td>new Climate Divisional (NOAA climate dataset)</td>
</tr>
<tr>
<td>NDBC</td>
<td>National Data Buoy Center</td>
</tr>
<tr>
<td>NDVI</td>
<td>Normalized Difference Vegetation Index</td>
</tr>
<tr>
<td>NDWI</td>
<td>Normalized Difference Water Index</td>
</tr>
<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>
<tr>
<td>Acronyms and Abbreviations</td>
<td></td>
</tr>
<tr>
<td>---------------------------</td>
<td>---------------------------</td>
</tr>
<tr>
<td>NICENET</td>
<td>Nevada Integrated Climate and Evapotranspiration Network</td>
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<tr>
<td><strong>NIDIS</strong></td>
<td>National Integrated Drought Information System</td>
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<tr>
<td><strong>NLDAS</strong></td>
<td>North American Land Data Assimilation System</td>
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<tr>
<td><strong>NMME</strong></td>
<td>North American Multi-Model Ensemble</td>
</tr>
<tr>
<td><strong>NOAA</strong></td>
<td>National Oceanic and Atmospheric Administration</td>
</tr>
<tr>
<td><strong>NOAH</strong></td>
<td>Neural Optimization Applied Hydrology</td>
</tr>
<tr>
<td><strong>Noah-MP</strong></td>
<td>Noah-Multi-parameterization Model</td>
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<tr>
<td><strong>NOHRSC</strong></td>
<td>National Operational Hydrologic Remote Sensing Center</td>
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<tr>
<td><strong>NPP</strong></td>
<td>Nonparametric paleohydrologic method</td>
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<tr>
<td><strong>NRCS</strong></td>
<td>Natural Resource Conservation Service</td>
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<tr>
<td><strong>NSIDC</strong></td>
<td>National Snow and Ice Data Center</td>
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<tr>
<td><strong>NSMN</strong></td>
<td>National Soil Moisture Network</td>
</tr>
<tr>
<td><strong>NVDWR</strong></td>
<td>Nevada Department of Water Resources</td>
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<tr>
<td><strong>NWCC</strong></td>
<td>National Water and Climate Center</td>
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<tr>
<td><strong>NWS</strong></td>
<td>National Water Information System</td>
</tr>
<tr>
<td><strong>NWM</strong></td>
<td>National Water Model</td>
</tr>
<tr>
<td><strong>NWP</strong></td>
<td>numerical weather prediction</td>
</tr>
<tr>
<td><strong>NWS</strong></td>
<td>National Weather Service</td>
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<tr>
<td><strong>NWSRFS</strong></td>
<td>National Weather Service River Forecast System</td>
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<tr>
<td><strong>NZI</strong></td>
<td>New Zealand Index</td>
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<tr>
<td><strong>OCN</strong></td>
<td>Optimal Climate Normals</td>
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<tr>
<td><strong>OHD</strong></td>
<td>Office of Hydrologic Development</td>
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<tr>
<td><strong>OK Mesonet</strong></td>
<td>Oklahoma Mesoscale Network</td>
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<tr>
<td><strong>ONI</strong></td>
<td>Oceanic Niño Index</td>
</tr>
<tr>
<td><strong>OWAQ</strong></td>
<td>Office of Weather and Air Quality</td>
</tr>
<tr>
<td><strong>OWP</strong></td>
<td>Office of Water Prediction</td>
</tr>
<tr>
<td><strong>PC</strong></td>
<td>principal components</td>
</tr>
<tr>
<td><strong>PCA</strong></td>
<td>principal components analysis</td>
</tr>
</tbody>
</table>
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>Description</th>
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<tbody>
<tr>
<td>SCAN</td>
<td>Soil Climate Analysis Network</td>
</tr>
<tr>
<td>SCE</td>
<td>Shuffled Complex Evolution</td>
</tr>
<tr>
<td>SCF</td>
<td>seasonal climate forecast</td>
</tr>
<tr>
<td>SE</td>
<td>standard error</td>
</tr>
<tr>
<td>SECURE</td>
<td>Science and Engineering to Comprehensively Understand and Responsibly Enhance Water</td>
</tr>
<tr>
<td>SFWMDC</td>
<td>South Florida Water Management District</td>
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<tr>
<td>SM</td>
<td>soil moisture</td>
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<tr>
<td>SMA</td>
<td>Soil Moisture Accounting</td>
</tr>
<tr>
<td>SMAP</td>
<td>Soil Moisture Active Passive</td>
</tr>
<tr>
<td>SMHI</td>
<td>Swedish Meteorological and Hydrological Institute</td>
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<tr>
<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>SNOTEL</td>
<td>Snow Telemetry</td>
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<td>SOI</td>
<td>Southern Oscillation Index</td>
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<tr>
<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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<tr>
<td>SRES</td>
<td>Special Report on Emissions Scenarios</td>
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<td>SRP</td>
<td>Salt River Project</td>
</tr>
<tr>
<td>SSEBOP</td>
<td>Simplified Surface Energy Balance</td>
</tr>
<tr>
<td>SSEBOP ET</td>
<td>Simplified Surface Energy Balance Evapotranspiration</td>
</tr>
<tr>
<td>SSP</td>
<td>Societally Significant Pathway</td>
</tr>
<tr>
<td>SST</td>
<td>sea surface temperatures</td>
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<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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<tr>
<td>SUMMA</td>
<td>Structure for Unifying Multiple Modeling Alternatives</td>
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<td>SVD</td>
<td>singular value decomposition</td>
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<td>SW</td>
<td>surface water</td>
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<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/Description</td>
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<td>---------</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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<tr>
<td>SWS</td>
<td>Statistical Water Supply</td>
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<tr>
<td>Tair</td>
<td>air temperature</td>
</tr>
<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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<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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<td>UCAR</td>
<td>University Corporation for Atmospheric Research</td>
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<td>UCBOR</td>
<td>Upper Colorado Bureau of Reclamation</td>
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<tr>
<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>
</tr>
<tr>
<td>USACE</td>
<td>U.S. Army Corps of Engineers</td>
</tr>
<tr>
<td>USBR</td>
<td>U.S. Bureau of Reclamation</td>
</tr>
<tr>
<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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<td>USGCRP</td>
<td>U.S. Global Change Research Program</td>
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<tr>
<td>USGS</td>
<td>U.S. Geological Survey</td>
</tr>
<tr>
<td>USHCN</td>
<td>United States Historical Climatology Network</td>
</tr>
<tr>
<td>VIC</td>
<td>Variable Infiltration Capacity (model)</td>
</tr>
<tr>
<td>VIIRS</td>
<td>Visible Infrared Imaging Radiometer Suite</td>
</tr>
<tr>
<td>VPD</td>
<td>vapor pressure deficit</td>
</tr>
<tr>
<td>WBAN</td>
<td>Weather Bureau Army Navy</td>
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<tr>
<td>WCRP</td>
<td>World Climate Research Program</td>
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<tr>
<td>WFO</td>
<td>Weather Forecast Office</td>
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<td>WPC</td>
<td>Weather Prediction Center</td>
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<tr>
<td>WRCC</td>
<td>Western Regional Climate Center</td>
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<tr>
<td>WRF</td>
<td>Weather Research and Forecasting</td>
</tr>
<tr>
<td>WRF-Hydro</td>
<td>WRF coupled with additional models to represent hydrologic processes</td>
</tr>
</tbody>
</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