Colorado River Basin Climate and Hydrology

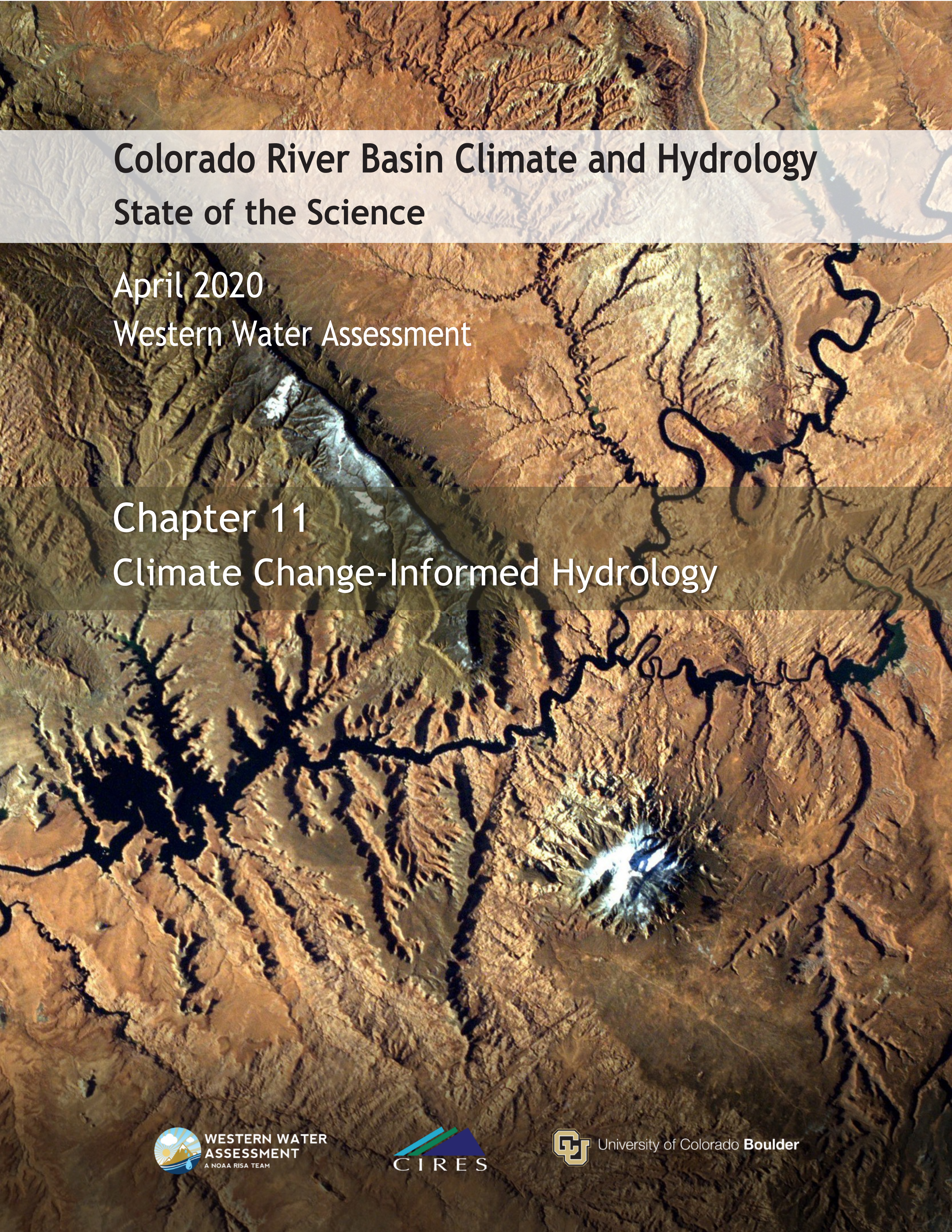
State of the Science

April 2020

Western Water Assessment

Chapter 11

Climate Change-Informed Hydrology



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University of Colorado Boulder

Colorado River Basin Climate and Hydrology
State of the Science

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Volume IV

Long-term—Informing the 5-Year to 50-Year Time Horizon

Volume IV of the Colorado River Basin State of the Science report focuses on models and methods for developing hydrologic traces that represent plausible hydrologic futures and can be run through system or planning models to evaluate the potential for outcomes and impacts of interest over the next 5 to 50 years. The three main approaches for developing such traces are Historical Hydrology (Chapter 9), Paleohydrology (Chapter 10), and Climate Change-informed Hydrology (Chapter 11). Long-term hydrologies generated using one or more of these approaches are used as driving inputs for Reclamation's CRSS planning model, as well as similar planning and system models used by other organizations. The three chapters in Volume IV provide comprehensive descriptions and assessments of the respective approaches and their variants, the data they require, their applications, and their tradeoffs. It is important to examine and understand these choices in order to select appropriate hydrologic traces for system modeling and risk, and also to interpret the output of system modeling that has already been performed.

Traditional long-term planning methods are based on the assumption that future hydrology will have characteristics (average, variance, extremes) similar to the historical observed hydrology. The extreme hydrologic drought of 2000–2004, unprecedented in the observed record, highlighted the downside of basing expectations for future hydrology only on the observed record (i.e. historical hydrology). Clearly, hydrologic behavior outside the range of the past 100 years was, and is, possible. Accordingly, the system analyses performed by Reclamation to support the 2007 Interim Guidelines included, for the first time, ensembles of hydrologic traces based on tree-ring reconstructions of basin paleohydrology. These traces show a broader range of natural variability, including more severe and sustained droughts, than those based only on the past century's observed hydrology (Chapter 2).

As the dry period that began in 2000 persisted, studies modeling the future impacts of human-caused climate change on basin hydrology consistently indicated that the 21st century was likely to see systematic shifts in hydrologic conditions: earlier snowmelt and runoff, lower runoff efficiency, and (with less certainty) a decline in annual streamflow. Because Reclamation and other basin stakeholders saw the need to explicitly represent this additional climate change risk in planning studies, Appendix U in the 2007 Interim Guidelines laid out a pathway for developing and using climate change-informed hydrologic traces. In 2012, the Basin Study formally incorporated a climate change-informed ensemble along with traces based on historical hydrology and paleohydrology, using Robust Decision Making techniques to assess risks from all scenarios on an equal footing.

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

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

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

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

Key characteristics of the main types of hydrology, observed, paleohydrology, and climate change-informed. (Source: adapted from Lukas et al. 2014)

	Historical hydrology (Chapter 9)	Paleohydrology (Chapter 10)	Climate change-informed hydrology (Chapter 11)
Most useful information to extract from this type of hydrology	Variability (interannual to decadal); recent trends	Variability (interannual to multi-decadal); shifts in mean and variability	Potential long-term future changes
Embedded assumption in using this to inform planning	Historical mean and variability is stable over time and is representative of future risk	Pre-1900 hydrology, including severe droughts and shifts in mean and variability, can recur in the future	Climate models can provide reliable information about future changes in the basin
Key data and models	Gaged observations of streamflow and major diversions; water-balance model to naturalize streamflow (except at headwaters gages)	Tree-ring chronologies (site time-series); statistical models relating ring-width to climate and hydrology	Global climate models, statistical downscaling and bias-correction methods; gridded climate data; regional climate models; hydrology models
Advantages	Provides baseline information about risk; relates other sources of information to our experience of system impacts; readily available, trusted, and well-vetted	Shows broader range of natural variability than seen in the observed records; places observed variability in longer context; provides many sequences of wet and dry years	Best source of information about potential effects of future climate change on hydrology
Limitations	Does not capture the full range of natural variability; does not reflect risk from future climate change; likely to underestimate future system stresses	Uncertainty in the proxy information; does not reflect risk from future climate change, though the broader range of variability may approximate that risk	Larger uncertainties in future changes, requiring consideration of many traces; complex datasets that are difficult to obtain, analyze and interpret
Primary sources of uncertainty affecting the output	Imperfect record of streamflows; inadequate characterization of depletions when naturalizing gage records	Tree rings imperfectly reflect hydroclimatic conditions; choices in handling of the tree-ring data and the model that relates tree-ring data to observed streamflows	Future emissions of greenhouse gases; differing climate models; choice of downscaling and bias-correction methods; differing hydrologic models

Chapter 11

Climate Change-Informed Hydrology

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Key points

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

11.1 Overview

The last decade has seen basin water planning activities increasingly informed by expected future climate change and its effects on hydrology. The development and use of climate change-informed hydrology was largely confined to the research community prior to 2010, with few applications in real-world water planning activities in the western U.S. Appendix U of the Final EIS for the Interim Guidelines (Reclamation 2007c) set a pathway for consideration of climate change projections and their incorporation in water planning for the basin. Since then, there has been a broad shift toward greater use of these data by water agencies at the federal, state, and local level in the Colorado River Basin and elsewhere in the West, although with substantial variation in the pace and extent of adoption by different agencies and stakeholders. There has also been rapid growth in methodologies and available datasets, with agencies such as Reclamation and U.S. Army Corps of Engineers (USACE) becoming directly involved with data development, and leading interagency efforts to advance both the science and practice in this area (Brekke et al. 2009; Brekke 2011; Raff et al. 2013). The Water Utility Climate Alliance (WUCA), a self-organized consortium of major municipal water utilities, and its partners have also been instrumental in facilitating the development of climate change guidance for water managers (e.g., Barsugli et al. 2009; Vogel 2015).

Climate change-informed hydrologic traces have been used as an adjunct to traces based on observed hydrology and paleohydrology in basin-scale planning studies, and also on their own to drive climate change impact assessments (see the Volume IV introduction). Virtually all approaches to developing climate change-informed hydrology, whether in the Colorado River Basin or elsewhere, begin with the output of GCMs—an acronym that originally referred to “general circulation models” but has come to also represent the more inclusive category “global climate models.” The GCMs translate the expected climate “forcings” (greenhouse gases, aerosols, and land use changes) on the Earth’s energy balance into future climate changes at global and regional scales, but they run at too coarse a resolution (typically 100 km or greater) to directly produce robust basin-scale hydrology outputs that are usable for water planning in the basin. Several different methods, involving varying intermediate steps and methodological choices, may be used to derive basin-scale climate change-informed hydrology from GCM output (Figure 11.1).

In the method that has been most often used, including in recent basin planning studies (e.g., Reclamation 2012e, 2018), emissions scenarios are used to drive GCMs, and the climate output of the GCMs is bias-corrected and downscaled, then run through a separate (off-line) hydrologic model (Figure 11.1; the pink arrows show this pathway). At each step, described in Table 11.1, there are subjective decisions that a modeler or data analyst must make, which partially indicates the uncertainties associated with that model or data type. The uncertainties collectively carry forward into the final result (simulated future hydrology), although not necessarily in a straightforward, additive manner.

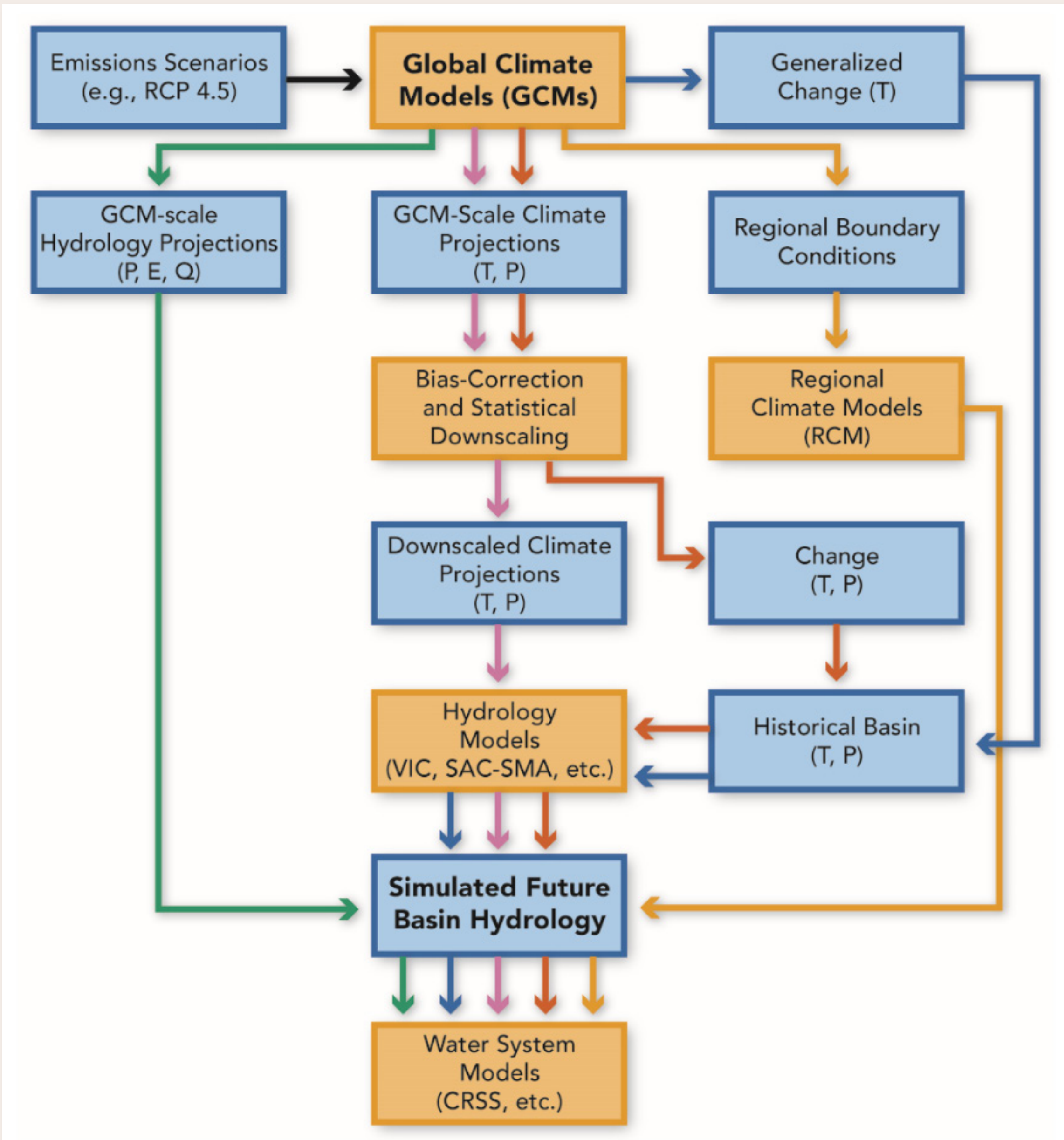


Figure 11.1

Schematic showing five different approaches (colored arrows) for developing climate change-informed hydrology from global climate model (GCM) output that have been tested or implemented for the Colorado River Basin. The pathway shown with the pink arrows has been the most frequently used in recent basin planning studies. Blue boxes show data inputs/outputs, while orange boxes show modeling steps. See also similar schematics in Ray et al. (2008) and Vano et al. (2014).

Table 11.1

Key steps in the typical pathway for producing climate change-informed projections of future hydrology, objective of that step, and challenges related to that step.

Step in modeling chain	Objective of this step	Caveats
Emissions scenarios	Provide multiple trajectories of future levels of global climate forcing (mainly from greenhouse gases) so that GCMs can project the future climate changes associated with an integrated storyline of future population growth, energy use, and policy.	Scenarios often have been lumped together in hydrologic impact studies, but this should be avoided. Probabilities have not been assigned to the scenarios.
Global Climate Models (GCMs)	Provide estimates of future changes in atmospheric circulation and in key climate variables, at global to continental scales.	The simulated natural (internal) variability in GCM projections means that large ensembles of simulations are required to robustly estimate mean changes.
Bias-correction	Shifts the values of GCM-simulated climate variables to better match historical observations of those variables (both mean and variability).	Some GCM biases cannot be meaningfully corrected. Bias-corrected data can mislead users about the ability of the underlying GCMs to simulate historical climate.
Downscaling	Translates coarse-scale GCM climate output statistically or dynamically into finer-scale climate output suitable for regional climate analysis and impacts modeling.	Most downscaling methods implicitly assume that spatial relationships or other characteristics of observed climate are maintained in the future (i.e., stationarity). Can mislead users about the reliability of the spatial and temporal details of the regional output.
Hydrologic modeling	Translates finer-scale climate output into future trajectories of hydrologic variables (e.g., runoff) at basin and watershed scale.	Hydrology models are calibrated to historical climate and may have stationarity assumptions embedded in their parameters.

Methods that develop basin-scale hydrologic simulations from GCMs in order to drive a water system model are aligned with "top-down" approaches to climate change impact assessment, where one starts with global-scale climate projections, ultimately arriving at local changes and impacts that are determined by those top-level inputs in combination with the intervening data and models. In comparison, "bottom-up" approaches typically begin with local system vulnerabilities to determine thresholds of undesirable impacts, then query higher-level climate information to assess the future changes in exceedances of system thresholds. In practice, climate impact or vulnerability assessments often end up as hybrids of top-down and bottom-up approaches. When one begins an assessment process with a large set (ensemble) of global climate projections, as is typically done, there is usually an equally large ensemble of local or basin-scale simulations at the end, with each of those simulations retaining important characteristics of the respective climate projection that drove it. The handling and interpretation of these simulations strongly influence how the data ultimately inform planning decisions.

The organization and content of this chapter acknowledges that the top-down, large-ensemble approach is strongly embedded in current practice, including recent and forthcoming hydrologic analyses and planning studies for the basin (e.g., Reclamation 2012e; 2018; 2020). Thus, this chapter follows the typical processing steps from GCMs to basin-scale hydrology, providing information on models and methods as used to generate ensembles of climate change-informed hydrology, and summaries and evaluations of the output of those ensembles. However, there are alternative approaches to using climate change information to understand potential future hydrology—those alternatives will be described toward the end of this chapter.

Those readers with greater familiarity with the processing steps and models (GCMs, emissions scenarios, downscaling) and who are most interested in the results—projected future climate and hydrology for the Colorado River Basin—are encouraged to jump ahead to sections 11.6 and 11.7.

11.2 Understanding GCMs and climate projections

As noted above, GCMs are the usual starting point for methods for producing climate change-informed hydrology, such as can be run in a water system model like CRSS. GCMs are designed to simulate the dynamics of the atmosphere, oceans, land surface and vegetation, sea ice, land ice, and the energy balance and water balance that integrate these components of the climate system. Overall, they provide realistic simulations of the key physical phenomena such as the planetary energy balance, large-scale atmospheric and oceanic circulation, broad-scale patterns of temperature and precipitation, and statistical characteristics of the historical and current climate, at global scales. At the scale of regions the size of the Upper Basin, the simulations are not as realistic, especially for precipitation, as detailed below.

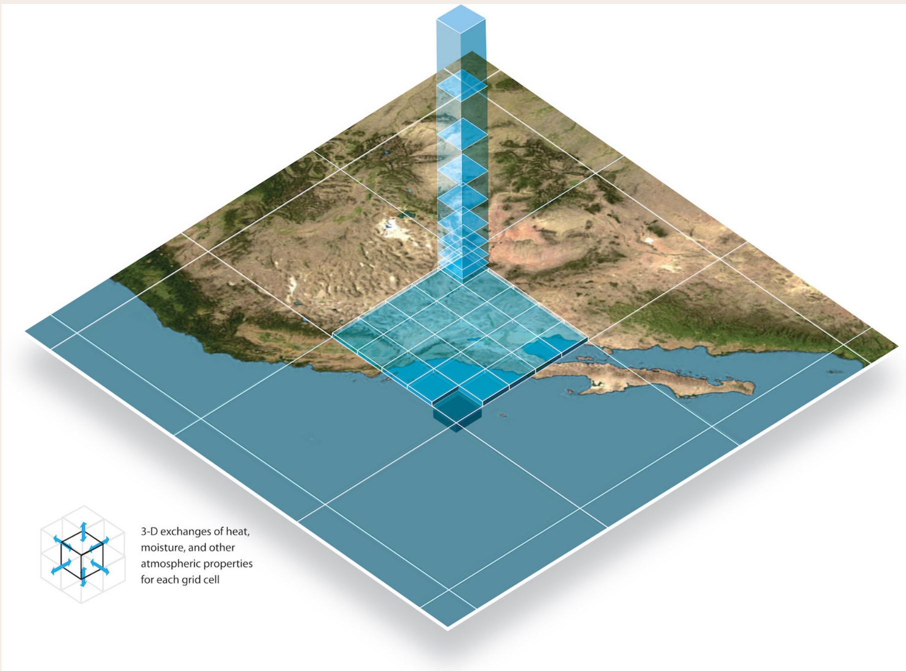


Figure 11.2

Schematic showing the 3-dimensional grid of a typical GCM, with a horizontal resolution of about 100 km, and multiple vertical levels extending up into the atmosphere and down into the oceans. (Source: University Corporation for Atmospheric Research.)

The typical structure of a GCM divides the globe—the atmosphere and oceans—into a grid in both the horizontal and vertical dimensions, creating grid boxes (Figure 11.2). In GCMs, as in weather and climate forecast models (Chapter 7), fundamental physical laws of thermodynamics, motion, and fluid dynamics are used to simulate many of the processes, such as the transfer of mass, energy, and momentum between the grid boxes. Other processes, such as the formation of clouds and thunderstorms, take place at spatial scales smaller than a model grid box (typically 100-250 km across). Climate models simulate these sub-grid-scale processes by using numerical factors (parameters) that have been generalized from observations to the grid box scale, a procedure called parameterization. Higher resolution (i.e., smaller grid boxes) allows for more physically explicit representation of processes, as well as more realistic depiction of topography, both of which tend to improve model performance. But higher resolution comes with much greater computational costs; increasing model resolution both horizontally and vertically by a factor of two requires eight times as many calculations.

From a handful of models at a few modeling centers in the 1980s, the GCM community has grown to over 30 modeling centers in 10 countries. These centers have developed and now maintain at least 60 GCMs. It is important to emphasize that these have not been wholly independent efforts; the modeling centers share model code and parameters for many processes, and several centers maintain multiple GCMs that are variants of each other.

Climate projections

For a given climate simulation, a GCM is initialized with a long period to "spin up" the ocean and other slowly evolving model components from specific starting observations of the atmosphere and oceans, and then the GCM is allowed to run freely in time to simulate the past climate or to make long-term projections of future climate. Climate models are marched forward from the initial state at time steps ranging from a few minutes to an hour. This high temporal resolution means that GCMs actually simulate sequences of hourly and daily weather, which integrate over time into modeled climate variability and change at longer timescales. After the initial state is specified, the only inputs to the GCM are so-called "external forcings," such as solar variations, aerosols from historical volcanic eruptions, and the changes in greenhouse gas concentrations, ozone, and anthropogenic aerosols collectively specified in an emissions scenario. Recently, historical observations and future scenarios of land cover change, which can exert regional influences on climate, have been included in many models.

A simulation of future climate from a GCM is called a projection, rather than a prediction or forecast, because it is conditional on a particular set of assumptions about future greenhouse gases and other climate forcings. The assumptions reflect an integrated storyline of future population growth, energy use, and policy (emissions scenarios; section 11.4). For any given climate variable, the GCM projection will show a combination of 1) simulated natural ("internal" or "unforced") variability and 2) a forced change over time, if that variable is affected by changes in external forcing (most prominently, rising greenhouse gases).

A critical difference among GCMs is how each one simulates the feedback mechanisms that are expected to amplify the direct forcing of the climate from greenhouse gases, mainly involving clouds and water vapor. The strength of these feedback mechanisms is uncertain, and thus the models show a range of global temperature responses to given increments of greenhouse gases, which then translates into similarly broad ranges for projected temperatures at regional scales.

GCM performance and credibility

Unlike short-term forecasts from weather models, which can be readily validated by frequent comparison with observations of the actual weather over the forecast period, the multidecadal future projections from climate models cannot be validated directly. Thus, the main way that the credibility of GCMs is established is by comparing their simulations of the historical period, over different spatial scales, with the observed climate over that period. Such comparisons examine both the models' reproduction of the statistics of climate—averages, ranges, and extremes—and the models' fidelity to the dynamical features of key climate processes. These comparisons can also be used to evaluate the relative performance of the GCMs, with the important caveat that performance over the historical period may not be reflective of a model's skill in accurately predicting the future changes in climate.

Assessing the ability of GCMs to reproduce the dynamical features and statistics of the historical climate, one can make the generalizations listed below (Barsugli et al. 2009; Lukas et al. 2014; USGCRP 2017; Reclamation 2020).

Performance at global to continental scales (1,000 km to 10,000 km)

What GCMs reproduce well in their raw output:

- Temperature: Spatial and seasonal patterns (i.e., monthly and annual averages), and recent warming trends
- Precipitation: Spatial and seasonal patterns (i.e., monthly and annual averages), but not as well as for temperature
- The dominant seasonal patterns of high and low pressure
- The jet stream and its seasonal north-south movement

What GCMs do not reproduce as well in their raw output:

- Precipitation: Daily amounts—too little variability ("GCM drizzle")
- ENSO: the pattern and cycle is present in nearly all models, but the spatial features are unrealistic in some important respects

Performance at the scale of the Colorado River Basin (<1,000 km)

What GCMs reproduce well in their raw output:

- Temperature: Seasonal cycle and recent warming trends

What GCMs do not reproduce as well in their raw output:

- Temperature: Spatial patterns—these are largely driven by topography which is smoothed out in GCMs
- Temperature: Regional annual average—can differ from observed by +/- 6°F
- Temperature: At mountain-top level—too warm because GCM-modeled mountains are too low

- Precipitation: Annual amounts—nearly all GCMs overestimate by 50-150%
- Precipitation: Seasonal cycle (monthly averages)—few GCMs replicate the observed pattern
- Precipitation: Spatial patterns—these are largely driven by topography which is smoothed out in GCMs
- Precipitation: Daily amounts—insufficient variability; heavy and extreme events are too small/infrequent
- ENSO signal in the region's precipitation—generally weaker than actual

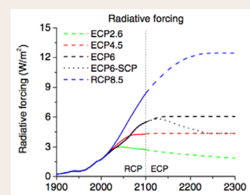
Many of the deficiencies listed above stem from the relatively coarse spatial resolution (>100 km) of most GCMs and their inadequate representation of the complex topography of the western U.S. These deficiencies can be addressed to varying degrees using regional downscaling methods (section 11.5), which also include a bias-correction step that corrects for the systematic errors in GCM-simulated temperature and precipitation described above.

11.3 The CMIPs: Standardized collections of GCM projections

In the 1990s, the global community of climate modelers recognized the need for standardized sets of climate model runs, with consistent inputs, time periods to simulate, and historical and future greenhouse gas scenarios; i.e., emissions scenarios (section 11.4). This would facilitate systematic evaluation of model outputs to improve understanding of climate dynamics and to improve the models themselves. These efforts evolved into the World Climate Research Programme's (WCRP's) Coupled Model Intercomparison Project (CMIP). The third phase, called CMIP3, was carried out to support the IPCC's Fourth Assessment Report (AR4), while the most recent phase, CMIP5 (there was no CMIP4), supports the IPCC Fifth Assessment Report (AR5). The next phase, CMIP6, is in progress and will support the IPCC Sixth Assessment Report, which is expected in 2021. A list of the modeling centers and the GCMs for which CMIP5 projections are available can be found on this NOAA webpage.

Each CMIP can be thought of as an organized roundup of the output of the latest (at the time) generation of GCMs. Nearly all GCM output used in regional and national climate assessments and in basin-scale water resource planning studies since 2008 have come from CMIP3 or CMIP5 or both. Compared to CMIP3, CMIP5 included more participating modeling centers and GCMs, generally higher-resolution models, more complete physical parameterizations of key climate processes and more individual

Models Represented in NOAA's Climate Change Web Portal



Link: https://esrl.noaa.gov/psd/ipcc/cmip5/help.html projections of future climate. It appears that CMIP6 will see the continuation of all of these trends. The differences between CMIP3, CMIP5, and CMIP6 are summarized in Table 11.2.

Table 11.2

Key characteristics of the Coupled Model Intercomparison Project (CMIP) and participating GCMs in Phase 3 (CMIP3), Phase 5 (CMIP5), and the forthcoming Phase 6 (CMIP6) and applications of GCM data from CMIP3 and CMIP5. (Source: updated from Lukas et al. 2014; CMIP6 information from Hausfather 2019)

	CMIP3	CMIP5	CMIP6
Initial data availability	2006	2012	2019-2020
Main Emissions Scenarios (count) See section 11.4 for explanation and acronyms	(3) *SRES:* B1, A1B, A2	(4) *RCP:* 2.6, 4.5, 6.0, 8.5	(9) *SSP-RCP:* SSP1-1.9, SSP1-2.6, SSP2-4.5, SSP3-7.0, SSP3-LowNTCF [6.3], SSP4-3.4, SSP4-6.0, SSP5-3.4-OS, SSP5-8.5
Historical climate period	1880–2000	1850–2005	1850-2014
Projection period	2001–2100	2006–2100+	2015-2100+
Number of modeling centers	16	30	49
Number of models	22	55	100
Number of model simulations (projections) for core future scenario runs	120	250	>300?
Range of horizontal resolutions (average grid cell size)	100-500 km (median: 250 km)	60–250 km (median: 150 km)	25–250 km
Timestep of archived data	Monthly	Daily and monthly; some sub-daily	Daily and monthly; some sub-daily
Decadal Prediction?	No	Yes, 2010–2035	Yes
Selected climate assessments using these projections	IPCC *AR4* (2007) *Climate Assessment of the Southwest* (2013) *Climate Change in Colorado* (2008)	IPCC *AR5* (2013) *National Climate Assessment* (NCA3, 2014; NCA4, 2018) *Climate Change in Colorado* (2014)	IPCC *AR6* (2021)
Selected Colorado River Basin hydrology studies using these projections	*Colorado River Water Availability Study–*Phase 1 (2012) *Colorado River Basin Supply and Demand Study* (2012)	*Colorado River Water Availability Study–*Phase 2 (2014) *Draft CMIP5 Report (Reclamation 2020)*	

Participation in CMIP is open to all modeling centers, limited only by their ability to use the standardized inputs for a given CMIP "experiment" and produce runs in the specified output format. There are no formal criteria for model quality, reliability, or skill. However, any model that was unusually poor at reproducing the historical climate, or produced future projections whose results were well outside the bounds of the other models, would be unlikely to be put forward for participation in CMIP by the modeling center that developed it (Knutti 2010; Knutti, Masson, and Gettelman 2013; Sanderson, Wehner, and Knutti 2017; Eyring et al. 2019).

As noted earlier, climate models are not independent of each other: they share assumptions, simulation methods, and even code and parameter sets, and during development they are compared to the same set of historical observations. Collaboration among modeling centers also means that models that have high skill tend to be the ones that perform similarly to other models (Sanderson, Wehner, and Knutti 2017). Consequently, the effective number of models (i.e., sample size) in the CMIP ensembles is smaller than the nominal number of models (Tebaldi and Knutti 2007; Knutti, Masson, and Gettelman 2013; Sanderson, Wehner, and Knutti 2017). Because the resulting ensembles of model projections are neither a random nor systematic sample of potential future climate, the distribution of future projected changes should not be treated probabilistically. This issue is explored at greater length in the last section of this chapter.

Is CMIP5 better than CMIP3? Will CMIP6 be better than CMIP5?

While GCMs have continued to improve from one generation to the next, in the recent update cycles this progress has been more incremental than fundamental. The projections archived in CMIP5 are generally better than those in CMIP3, according to various performance metrics, but not so much better as to invalidate the results of analyses done with CMIP3 (Knutti et al. 2010; Lukas et al. 2014; Reclamation 2020). The CMIP3 and CMIP5 model ensembles show very similar average projections for temperature and precipitation changes over much of the globe, including most of North America, and a similar range of uncertainty across the models. For the Colorado River Basin, there was very little difference in the temperature projections between the CMIP3 and CMIP5 ensembles, after accounting for the differences in the emissions scenarios, but for precipitation, the CMIP5 projections were slightly shifted toward wetter outcomes than CMIP3, and this difference is accentuated by certain downscaling methods, as described later.

Similarly, the forthcoming CMIP6 models and their projections will be improved from CMIP5 in some technical respects (e.g., model resolution), and will probably have overall better performance in reproducing features of the observed climate. But judging from the previous CMIPs, CMIP6 should be expected to show similar spatial patterns of future change as

CMIP5 and CMIP3, and similarly broad ranges of future change, as CMIP5 and CMIP3. In other words, the overall CMIP6 ensemble seems unlikely to reduce uncertainties related to model structure (Table 1.4).

Enough of the CMIP6 model results have been released for analysts to discern that the CMIP6 models are showing, on average, warmer future global temperatures than CMIP5 given equivalent emissions scenarios (Hausfather 2019). This indicates that, compared to their CMIP5 counterparts, many of the CMIP6 models are simulating even stronger positive feedbacks (e.g., from clouds, water vapor, and surface reflectivity) that enhance the direct warming from the additional greenhouse gases. However, Tokarska et al. (2020) found that the CMIP6 models with higher future warming also tend to overestimate the observed global warming trend from 1981–2017; adjusting the CMIP6 projections to account for this tendency brings the overall CMIP6-projected warming into line with that depicted by CMIP5. It is too soon to know whether the adjustment to the CMIP6 ensemble proposed by Tokarska et al. (2020) will be more broadly accepted, e.g., to be implemented in downscaled CMIP6 datasets developed for application purposes.

In addition to the main set of 21st century climate projections from CMIP6 intended for use in climate change assessment ("ScenarioMIP"; O'Neill et al. 2016), there will be a separate set of projections run using high-resolution climate models ("HighResMIP"; Haarsma et al. 2016). At least 20 GCMs that run at 50-km horizontal resolution or better are participating in HighResMIP; this resolution is comparable to the regional climate models in NARCCAP and NA-CORDEX (see section 11.5). HighResMIP may be able to provide additional insights into potential changes in atmospheric and ocean dynamics influencing the western U.S.

SPOTLIGHT

Screening and weighting the GCM ensemble

The large size of the CMIP3 and CMIP5 ensembles (20–35+ GCMs, 100–200+ projections) and the broad range of projected future changes across the ensembles, make it challenging to analyze and interpret future climate projections. It would seem logical to try to reduce the size or otherwise refine the CMIP ensembles by evaluating the performance of the GCMs and then culling models that perform poorly or weighting the model projections according to their performance. For the most recent National Climate Assessment (USGCRP 2017), the GCM projections were weighted, but not screened to reduce the ensemble.

Over the past decade, researchers have tested different approaches for evaluation, screening, and weighting for projections of future climate for the western U.S. (Brekke et al. 2008; Pierce et al. 2009; Mote et al. 2011; Reclamation 2020; Rupp et al. 2013; Rupp, Abatzoglou, and Mote 2017). Nearly all of these efforts have found that weighting or screening the GCM ensemble has little or no effect on the distribution of future climate changes, assuming at least 10 of the models (i.e., 30-50% of the original ensemble) are retained. Also, looking across those efforts, one can see that performance rankings of models can vary with different performance metrics. In all cases, as mentioned earlier, those metrics are based on the model's ability to reproduce average statistics and spatial patterns of the observed climate, with the implicit but untestable assumption that models that better simulate the observed climate will perform better in predicting future climate changes.

For performance-based screening and weighting to have a significant and meaningful effect on the ensemble, there must be a clear relationship between model performance and the sign/magnitude of the model's projected future change. This condition, however, is rarely met in evaluations of GCM performance, including the case discussed in more detail below. One exception was from Rupp, Abatzoglou, and Mote (2017), who found that the GCMs that better reproduce the historical climate of the Columbia River Basin tend to project greater warming and larger precipitation increases than the other GCMs, though these results depended on the method of evaluating the GCMs.

If a screening procedure does reduce the original ensemble to fewer than 10 models (i.e., eliminating more than 70% of the 30+ CMIP5 models) any theoretical beneficial effect of screening out low-performing GCMs may be outweighed by the risk of under-sampling model uncertainty. In other words, the screened ensemble distribution may become too narrow, and exclude outlying but still plausible climate outcomes that one would want to consider in risk assessment and planning (Mote et al. 2011).

Comprehensive and basin-specific screening and weighting procedures were performed for the forthcoming report, '"Exploring Climate and Hydrology Projections from the CMIP5 Archive" (Reclamation 2020). A set of 52 CMIP3 and CMIP5 GCMs were first screened against global performance metrics (Gleckler, Taylor, and Doutriaux 2008; Flato et al. 2013), removing 13 of the models. The remaining 39 models (12 from CMIP3, 27 from CMIP5) were then assessed against a set of 48 region-specific metrics that address the ability of the GCM to reproduce 1) the basic statistics of Colorado River Basin temperature and precipitation; 2) the amplitude and phase of seasonal cycles of temperature and precipitation; and 3) ENSO and PDO mean Sea Surface Temperature (SST) pattern and signal spectrum, and the teleconnected temperature and precipitation response over the western United States. The output of the retained 39 GCMs was then weighted according to overall performance on the set of region-specific metrics, with the best-performing GCM being given roughly 2.5 times the weight of the worst-performing GCM.

The projections of hydrologic changes shown by the different ensembles—"Full" (all GCMs), "Retained" (after screening against the global metrics), and "Retained and Weighted" (after evaluation against the regional metrics)—are shown in Figure 11.3. There are only slight differences in the distribution of streamflow changes after the initial screening, and even smaller differences imparted by the weighting procedure (column on far right).

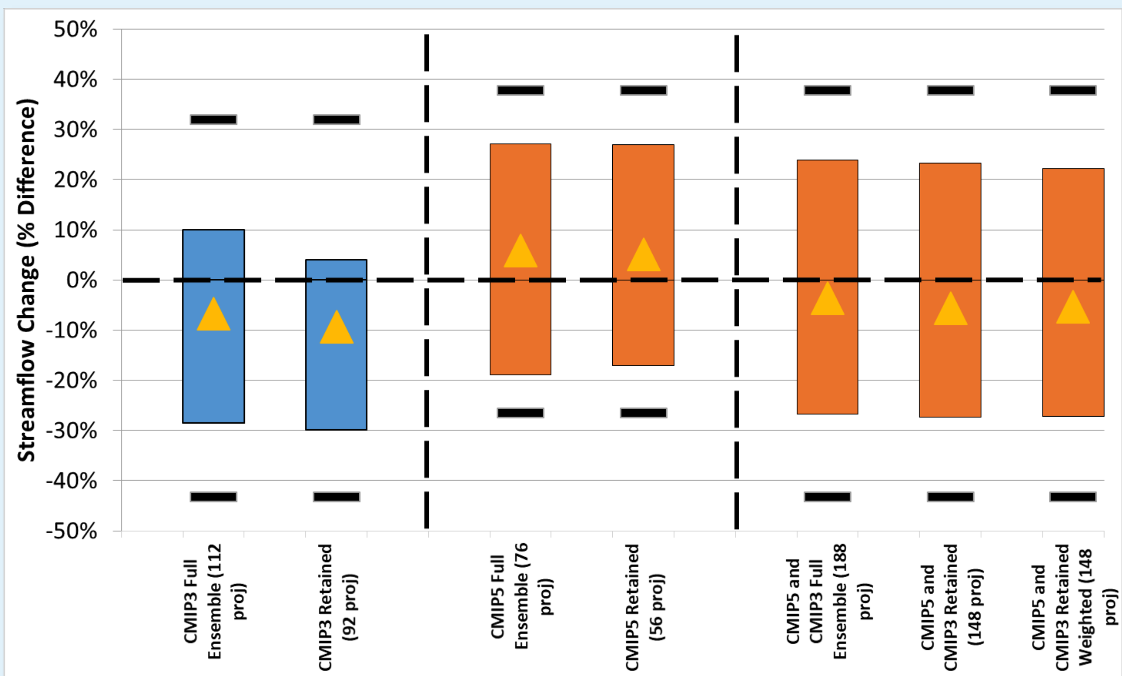


Figure 11.3

Projected changes in VIC-modeled streamflows at Colorado River at Lees Ferry for the end-of-century period (2066–2095) relative to the historical period (1971–2000), from the Full, Retained, and Retained and Weighted CMIP3 and CMIP5 GCM ensembles. Triangles are ensemble means, bars show the 10th and 90th percentiles range, and horizontal lines are minimum and maximum projections. (Source: Reclamation 2020)

Given the apparent lack of impact on the distribution of projected changes in climate and hydrology, the main value to screening and weighting procedures may be in imparting greater credibility to the results. Since screening and weighting of CMIP3 and CMIP5 GCMs specific to the Colorado River Basin has already been performed (Reclamation 2020), it makes sense for those refined ensembles to be used in future analyses for the basin. Potentially, the same analyses could be performed for the CMIP6 models when those data become available, though the value of doing so would likely be more in identifying performance differences between CMIP6 and CMIP5, than in refining the CMIP6 ensemble itself.

11.4 Emissions scenarios used to drive GCMs

Since anthropogenic greenhouse gas emissions have been identified as the primary cause of recent global warming and other climate changes (USGCRP 2017), it is necessary for future climate simulations from GCMs to have inputs that describe how greenhouse gas emissions and concentrations will unfold over the next century and longer. A single "best" forecast of future emissions would be fraught with very large uncertainties, so the modeling community has adopted a set of multiple standardized trajectories whose range is intended to capture those uncertainties.

The CMIP5 standardized greenhouse gas trajectories are called Representative Concentration Pathways (RCPs), which replaced the SRES (Special Report on Emissions Scenarios) emissions scenarios (e.g., B1, A1B, A2) that were used in the GCM projections for CMIP3. Both the RCPs and the SRES scenarios provide plausible trajectories of GHG emissions and concentrations that are each linked to future trends in demographic, socioeconomic, technological, and political factors. Since those underlying trends cannot be predicted with any confidence, there have been no probabilities assigned to any one of these RCPs being the actual future path.

Each CMIP5 GCM simulation or projection uses one of the four RCPs: RCP 2.6, RCP 4.5, RCP 6.0, or RCP 8.5 (Figure 11.4). The numbers refer to the strength of the global radiative forcing by year 2100, in watts per square meter (W/m^2)—the extra energy trapped in the climate system by added greenhouse gases and other human-caused changes—compared to pre-industrial levels. As with the SRES scenarios, the divergence among the RCPs at mid-century is much smaller than later in the century. The projected increase in global average temperature by 2100 for any given GCM closely corresponds to the radiative forcing of each RCP.

- RCP 2.6 (low) assumes immediate and very large (about 70%) reductions in GHG emissions from today's levels, and its climate forcing peaks by 2050 with CO_2 levels at about 435 parts per million (ppm), about 20 ppm above today's (2019) level. After 2050, the forcing trajectory of RCP 2.6 is well below the other RCPs.
- RCP 4.5 (medium-low) assumes large reductions in GHG emissions that are less drastic and take effect later than in RCP 2.6, with CO_2 at about 475 ppm at 2050 and rising. At 2050 the forcing of RCP 4.5 is slightly above RCP 6.0, but after 2070 it levels out so that it is below RCP 6.0.
- RCP 6.0 (medium-high) assumes moderate reductions in emissions, and its forcing is very similar to RCP 4.5 at 2050 and continues to climb throughout the 21st century.

- RCP 8.5 has greater forcing than the other RCPs at 2050, with CO_2 at about 530 ppm, and the gap increases over the second half of the 21st century. By 2100 RCP 8.5 has CO_2 levels around 950 ppm, over double the 2019 level. RCP 8.5 assumes essentially no reduction in emissions.

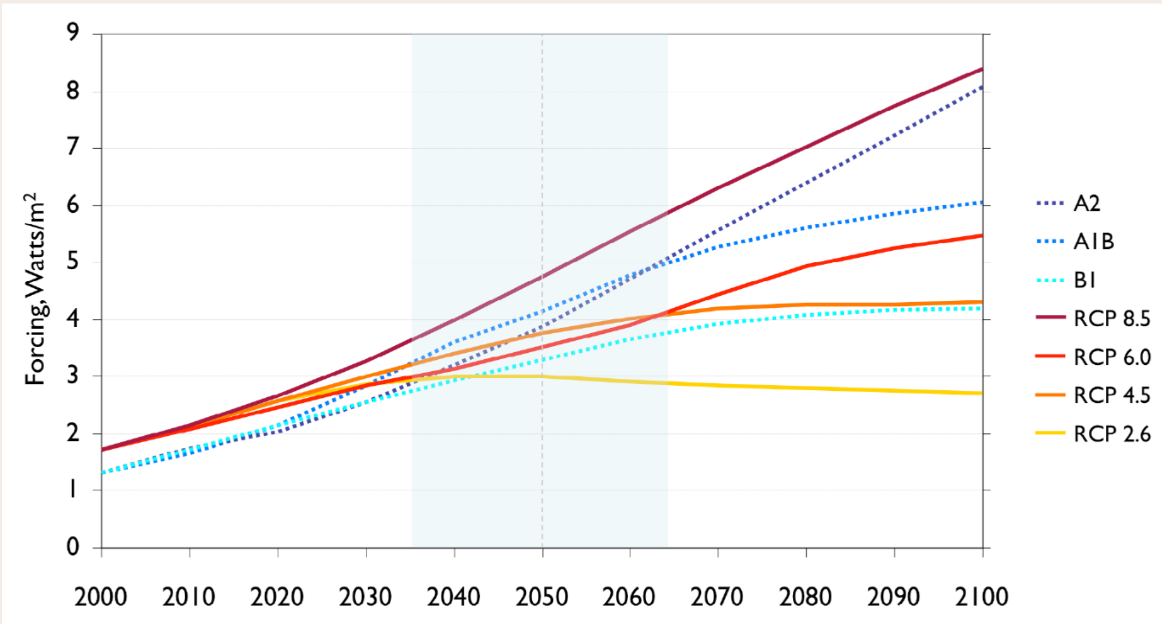


Figure 11.4

Global radiative forcing, 2000–2100, of the four Representative Concentration Pathways (RCPs) used to drive the current-generation (CMIP5) climate models and the three main SRES emissions scenarios used to drive the previous-generation (CMIP3) climate models. The CMIP6 model projections are being driven by slight variants on the four CMIP5 RCPs, along with five other emissions scenarios. (Source: Lukas et al. 2014; Data: SRES: IPCC 2000; RCP: IIASA RCP Database; http://tntcat.iiasa.ac.at:8787/RcpDb/)

For CMIP6, in the core future projections ("ScenarioMIP"), the RCPs have been retained, and each will be cross-referenced with an SSP (Societally Significant Pathway). For the CMIP6 projections, the climate forcing trajectories from 2020–2100 of these four RCPs are slightly different than in CMIP5 (Figure 11.3), so precise comparisons between CMIP5 and CMIP6 projections at mid-century are not quite apples to apples, although the climate forcings at end of the century will be the same. The 4 RCP-SSP scenarios are augmented by 5 additional SSP-based emission concentration scenarios which, like the current RCPs, have a specified century-end climate forcing level. These 5 scenarios will fill in the gaps between the 4 current RCPs, with forcings of 1.9, 3.4 (two scenarios), 6.3, and 7.0 W/m^2, respectively. It is not yet known how many individual GCM projections will be made available from each of the CMIP6 RCP-SSP scenarios.

While the RCPs were intended by their developers to be treated as though they were equally likely to occur, many impact assessments based on CMIP5 GCM output have excluded projections based on RCP2.6, including the forthcoming '"Exploring Climate and Hydrology Projections from the CMIP5 Archive" report (Reclamation 2020). The draft report noted that RCP2.6 represents an aggressive global emissions mitigation effort and has no analog among the SRES scenarios. The RCP2.6 trajectory requires the implementation of direct CO_2 capture and removal by the end of the century (van Vuuren et al. 2011).

On the other end of the scale, RCP 8.5 is often called the "business-as-usual" scenario, but it was derived from a larger family of "business-as-usual" scenarios (i.e., policies toward global carbon mitigation are not pursued), and RCP 8.5 tracks higher than most of them. Some researchers argue that a return to coal's dominance of primary energy supply as assumed in RCP 8.5 is increasingly unlikely (Ritchie and Dowlatabadi 2017). It is more appropriate to call RCP 8.5 a "high-end" business-as-usual scenario. Hausfather and Peters (2020) argue that the RCP8.5 trajectory has become highly unlikely due to recent trends in energy use and emissions, and it should be de-emphasized in impacts assessment.

Regardless of whether GCM data from all RCPs is used for analysis, keeping the GCM data driven by each RCP separate throughout the analysis chain allows one to more clearly identify the differences and uncertainty in the final hydrology output that is due only to the RCP. While there is substantial overlap in the ensembles of Colorado River Basin future streamflow generated using RCP 4.5 and RCP 8.5 projections (Figures 11.12 and 11.13), there are also systematic differences associated with the RCP.

11.5 Downscaling and regional climate projections

Overview of downscaling

The "raw" output from GCMs provides our best estimates of future changes in global circulation patterns and can paint a useful broad-brush picture of changes at the global to sub-continental scales (e.g., Figures 11.8 and 11.9 later in this chapter). But the coarse spatial resolution of GCMs makes the raw output less appropriate for analysis of watershed-scale changes, particularly for precipitation. This is especially true in areas of high topographic relief, such as the western U.S. Because the topography of mountain ranges is highly smoothed in the coarse representation of surface features in GCMs, with too-low elevations at the range crests, GCMs poorly simulate orographic precipitation and snow accumulation, and thus runoff from snowmelt—a critical deficiency in the snowmelt-driven Colorado River Basin. Other processes that control local precipitation and temperature in the basin (Chapter 2), such as land-atmosphere feedbacks, local slope circulations, convective processes, and regional monsoon circulations, are either poorly simulated by the GCMs or occur at spatial scales smaller than the typical GCM grid box.

To address these and other deficiencies in the GCMs, researchers have developed a number of methods to project regional-scale and local-scale changes in climate, using the raw GCM output as a starting point. These regional climate or *downscaling* methods have two primary purposes: first, to produce realistic daily or monthly sequences of weather and climate over regions such as the Colorado River Basin that can be used to run hydrology models and other impacts models, and second, to understand the regional changes that are likely to take place and the mechanisms behind them. The first is a relatively easy technical problem, for which most downscaling methods are sufficient. The second is a much harder and perhaps more important problem, and it is also difficult to quantify how well the different methods meet this goal.

Regional climate or downscaling methods are typically classified into one of two distinct categories: *dynamical* or *statistical* (Wilby and Wigley 1997). The dynamical approach requires running a higher-resolution regional climate model (RCM) over the domain of interest. This has the benefit of producing future projections that are more firmly grounded in our physical understanding of the processes involved, but at a cost of much higher computational resources. In contrast, statistical downscaling approaches typically require little in the way of total computing time, but they are based purely on statistical relationships among observed climate variables, and may not represent future changes in those variables correctly. The calibration of RCMs requires comparison with observed climate variables, so dynamical downscaling is not entirely free from this issue either.

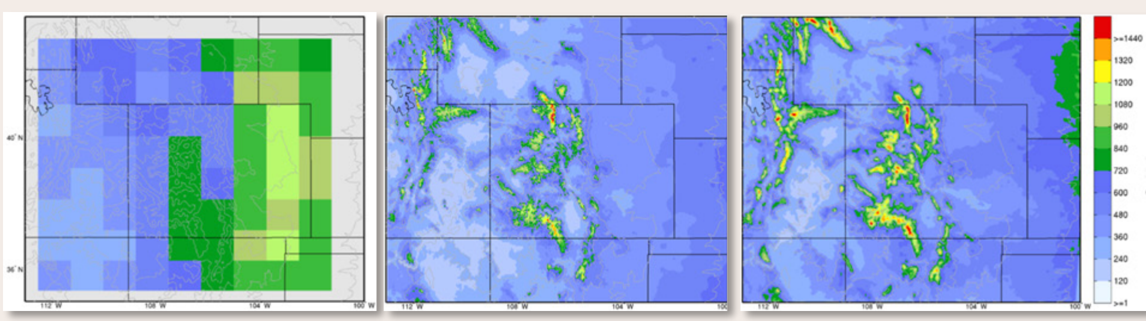


Figure 11.5

Historical average annual precipitation over the Upper Colorado River Basin and adjacent High Plains as simulated by the CESM GCM (100-km grid, left), as estimated by the PRISM observational gridded product (4-km grid, middle), and as simulated by the WRF high-resolution regional weather/climate model (4-km grid, right) which was used to dynamically downscale the CESM GCM simulation on the left.

For the Colorado River Basin, biases in GCMs make raw GCM output data problematic to use directly in hydrology models. Figure 11.5 shows that the mean annual precipitation coming from the Community Earth System Model (CESM; Hurrell et al. 2013), one of the higher-resolution GCMs, is not only of much coarser resolution than the spatial scales represented in the observed climate, it is also heavily biased (i.e., much too wet in the wrong places) and the spatial patterns would not match the spatial patterns of a coarsened observation dataset. In contrast, a very high resolution (4-km) regional climate model simulation using the Weather Research and Forecasting model (WRF; Skamarock and Klemp 2008) reproduces the annual precipitation field of the observations with much better spatial fidelity, and smaller biases. Most statistical downscaling methods also reproduce the observed spatial pattern, but only because they are forced to do so by design, not as a result of accurately simulating the underlying physical processes.

These biases in the GCMs are of critical importance for hydrologic applications. Most obviously, the fact that the GCMs do not properly represent the correct distributions of precipitation and temperature means that a hydrology model run directly with the output of that GCM will not develop a realistic snowpack, and so will not depict the correct magnitude or timing of spring runoff. In essence, such a hydrologic simulation would not be simulating the Colorado River Basin as we know it. That the mountains in a GCM are too low also means that the GCM will not simulate most precipitation in mountainous regions by orographic processes, as it should, but instead is more heavily reliant on simulated convection (i.e., thunderstorms) to generate precipitation. As such, it is possible that the global model would not predict the correct change in precipitation for this region, even if it is predicting the correct change in global circulation (e.g., shift in storm tracks) governing that precipitation. Also, local temperature change signals in the Colorado River Basin are strongly influenced by land surface feedbacks, such as the snow-albedo feedback, that are not present in the GCMs simply because the GCM mountains are not tall enough to maintain a seasonal snowpack in the first place.

Downscaled output variables

The most commonly provided variables from both statistical and dynamical downscaling models are daily precipitation and minimum and maximum temperatures. These variables have been the core of climate projections, in part because observations are available to train statistical methods to predict these variables. In addition, dynamical and quasi-dynamical methods, and some statistical methods, can provide downscaled humidity, shortwave and longwave radiation, and winds, though the lack of widely available observations of these variables means that there has not been as much verification and adjustment to correctly represent these variables.

Requirements for hydrologic modeling

Again, the first task of regional climate projection methods is to produce realistic sequences of weather and climate over regions such as the Colorado River Basin that can be used to run hydrology and other impact models. To be useful for hydrologic modeling, regional climate projections must first provide a high enough spatial and temporal resolution to resolve the hydrologically relevant phenomena. Statistical downscaling methods typically strive for a grid spacing less than or equal to 12 km, and a daily time sequence. A daily weather sequence is often further downscaled temporally to a 1- to 3-hourly sequence based on an idealized diurnal cycle for temperature and radiation, though precipitation often remains at the daily average time scale. This is sufficient to resolve large-scale storm systems, though not the more extreme convective processes (i.e., thunderstorms). The spatial and temporal resolution of a downscaled dataset is also driven by the gridded historical climate data available to train the statistical methods (Chapter 4).

An additional element required for robust hydrologic projections is that the daily to seasonal statistics of the historical regional climate as output from the downscaling method should be consistent with the historical climate data that were used to calibrate the hydrologic model. This can be approached by calibrating the hydrologic model using a dataset that is consistent with the downscaling method, or tuning the downscaling method to be consistent with the dataset that was used to calibrate the hydrologic model. For example, the continental-domain VIC parameters used in many climate projections are semi-calibrated using the Maurer gridded observation product (Maurer et al. 2002) as inputs, and the BCSD downscaled projections described below were trained on the Maurer gridded observations as well (Reclamation 2014).

All hydrologic models require, at a minimum, daily or monthly precipitation and temperature. More sophisticated hydrology and land surface models (Chapter 6) typically require shortwave and longwave radiation, humidity, and wind speed, preferably on an hourly time step. If only daily precipitation and temperature are available, then these additional variables are estimated. This estimation is commonly performed using a set of empirical equations as part of the MT-CLIM algorithm (Running and Thornton 1996); for example, MT-CLIM is embedded in the VIC hydrologic model. MT-CLIM uses a set of calibrated relationships to derive these variables from precipitation and minimum and maximum temperature; however, the viability of these relationships in a future climate has not been thoroughly evaluated. Wind is not estimated by MT-CLIM and is often simply given a climatological average value.

Widely used regional climate downscaling methods and datasets

Many different methods for regional downscaling of GCM output have been developed. The focus below is on those that have been most widely used in impact assessments for water resources and similar applications in the U.S. Publicly available datasets of downscaled projections produced using these methods are summarized in Table 11.3.

Statistical methods

The development of statistical downscaling methods is closely linked with applications in hydrology and water management (Wilby, Hassan, and Hanaki 1998; Wood et al. 2004). Interestingly, these two early works took very different approaches. The Statistical DownScaling Model (SDSM; Wilby, Dawson, and Barrow 2002) uses atmospheric variables that are more robustly simulated by the GCMs, such as humidity and upper-level winds, to predict precipitation.

In contrast, the Bias-Corrected Spatial Disaggregation method (BCSD; Wood et al. 2004) makes use of the GCM precipitation fields, in part because precipitation provides the most direct relationship with hydrologic variables of interest such as runoff (Clark and Hay 2004). More recently constructed analog approaches, including the Locally Constructed Analog method (LOCA; Pierce, Cayan, and Thrasher 2014), have been developed to make use of the spatial patterns of precipitation and temperature simulated by the GCMs to predict changes in regional climate. The focus here is on the two most commonly used statistical methods for water resource applications in the western U.S.: BCSD and LOCA, and also describe key differences between LOCA and two related techniques, BCCA and MACA. In considering any downscaling or regional climate method it is critical to understand the assumptions that the method makes about what information can be used from a GCM.

The statistical downscaling methods used in the United States have mainly been developed through short-term grant-based projects by researchers based at universities, and also at government agencies, often for specific regional applications. Their initial downscaled projection datasets, therefore, may only have regional coverage. An agency-university consortium led by Reclamation later employed the BCSD, BCCA, and LOCA methods to generate new datasets covering the contiguous U.S., facilitating broader use in water resources management and planning.

Table 11.3

Selected widely used and publicly available datasets of downscaled climate projections covering the conterminous U.S. or larger domains that are based on the downscaling methods discussed in this chapter. See the text for references to technical literature describing these methods and datasets. Note that there may be other available datasets produced using the same methods or variants of them. Time step M=monthly, D=daily

Dataset name	Downscaling Method	GCM data	Observed climate data for bias-correction	# Runs	Spatial Resolution	Time step	Associated hydrology-model output available?	Visualization tool that shows these data?
Statistically downscaled datasets								
Reclamation et al. CMIP5 BCSD	Bias-Corrected Spatial Disaggregation	CMIP5; 37 GCMs	Maurer et al. (2002)	231	12 km	M	Yes	No
NASA NEX-DCP30 (in USGS Nat'l Climate Change Viewer)	Bias-Corrected Spatial Disaggrega--tion (variant)	CMIP5; 33 GCMs	PRISM	>100	0.8 km	M	Yes	Yes – USGS National Climate Change Viewer
Reclamation et al. CMIP5 LOCA	Locally Constructed Analogs	CMIP5; 32 GCMs	Livneh et al. (2015)	64	6 km	D	Yes	Yes – NOAA Climate Explorer v2
Reclamation et al. CMIP5 BCCA	Bias-Correction Constructed Analogs	CMIP5; 32 GCMs	Maurer et al. (2002)	134	12 km	D	Yes	No
MACAv2, U. of Idaho (2 variants)	Multivariate Adaptive Constructed Analogs	CMIP5; 20 GCMs	METDATA; Abotzoglou (2013), or Livneh et al. (2013)	40	4 km, or 6 km	D	No	Yes; Climate Toolbox Climate Mapper
Dynamically downscaled datasets								
NARCCAP	Dynamical; 6 RCMs	CMIP3; 4 GCMs	Maurer et al. (2002)	12	50 km	D	No	No
NA-CORDEX	Dynamical; 6 RCMs	CMIP5; 6 GCMs	METDATA; Abatzoglou (2013)	35	25 km or 50 km	D	No	No

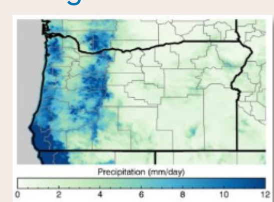
Bias-Corrected Spatial Disaggregation (BCSD). The Bias-Corrected Spatial Disaggregation method (BCSD) has been the most widely used statistical downscaling method in water management in the U.S., including in the Colorado River Basin, due to its longevity and its early adoption (in 2007) by the Reclamation-led consortium. BCSD was developed in the early 2000s to produce regional climate data that are consistent with the observed historical weather and climate, and the long-term, large-scale climate change signal predicted by GCMs. The standard implementation of BCSD uses quantile mapping (Panofsky and Brier 1968) to bias-correct the GCM monthly precipitation and temperature outputs to match an observed gridded climate dataset (e.g., Maurer at 1/8°; see Chapter 4). This bias-corrected dataset is then spatially disaggregated (i.e., downscaled) using historical climatological factors statistically relating each high-resolution (12-km) grid point to the encompassing coarse-resolution value from the GCMs, resulting in monthly downscaled projection values.

A further set of steps is used to generate daily downscaled output, if desired. A projected monthly value as generated in the steps above is used to select a similar month of historical weather from the observed gridded climate dataset, and that sequence of daily weather is rescaled for precipitation, or offset for temperature, to match the monthly values of the downscaled projection dataset. Effectively, this implies that the sequences of monthly precipitation and temperature predicted by the GCM are reasonable and can be relied on, but that the sequences of daily weather from the GCM are not reliable. However, it means that the projected weather sequences under a future climate will not substantially change, even if the underlying GCMs indicate such changes. A variant of BCSD using daily, rather than monthly, GCM data as inputs to produce daily projection data was subsequently applied by Abatzoglou and Brown (2012). This variant method implicitly assumes that the sequences of daily weather from the GCM are in fact reliable.

There have been numerous modifications and variants to the basic BCSD method over time to improve the representation of specific features, including a monthly dataset (NEX-DCP30) produced at 800-m resolution (Thrasher et al. 2013). The details of the most recent implementations of the BCSD by the Reclamation-led consortium can be found in Reclamation (2014).

Users of BCSD are cautioned that in the standard implementations of the method, such as those used by the Reclamation-led consortium, the quantile mapping procedure used for bias correction can alter the GCM-projected future change in precipitation, in a manner that does not appear to be physically meaningful. This issue is described in greater detail below.

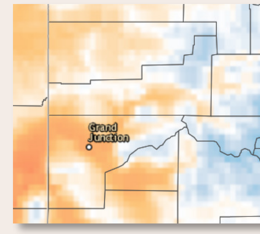
National Climate Change Viewer



Link:
https://www2.usgs.gov/landresources/lcs/nccv/viewer.asp

Locally Constructed Analog method (LOCA). The Locally Constructed Analog method (LOCA; Pierce et al. 2015) is a much newer statistical downscaling method that has gained widespread use in the western U.S. in the past several years. LOCA was developed to improve on previous "constructed analog" techniques that all make use of the coarse spatial pattern of the daily weather sequences from GCMs to generate a high-resolution spatial pattern. LOCA uses a very different initial bias-correction step from BCSD, with a frequency-dependent delta-quantile bias correction, similar to that described by Li, Sheffield, and Wood (2010), that corrects not only the statistical distribution, but also the representation on multiple time scales.

The Climate Explorer



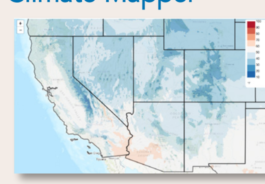
Link: https://crt-climate-explorer.nemac.org/

Once the bias correction is performed on the coarse scale, LOCA downscales the dataset by finding observed historical analog days with spatial patterns of precipitation or temperature that match the GCM's coarse resolution spatial patterns. It does this in two steps, and independently for each location; first it selects a collection of, for example, 30 days that match the larger regional pattern (within ~1000 km) around the location to be downscaled, and from those days, LOCA selects the single analog that best matches the more local precipitation or temperature pattern (within ~100 km). The available LOCA dataset used the Livneh et al. (2015) observational dataset on a 1/16° spatial grid to provide a higher spatial resolution dataset than common BCSD products. Unlike BCSD, LOCA assumes that the daily weather sequencing from the GCM is reasonable to begin with. So LOCA permits the daily "weather" to change, and as a result it can change, for example, the average number of storms in a year more than BCSD is likely to.

As with BCSD, more comprehensive overviews of LOCA are available to the reader seeking additional detail on the method (Pierce, Cayan, and Thrasher 2014; Pierce et al. 2015; Reclamation 2016a).

Bias-Corrected Constructed Analog (BCCA) and Multivariate Adaptive Constructed Analog (MACA). BCCA (e.g., Hidalgo, Dettinger, and Cayan 2008) and MACA (Abatzoglou and Brown 2012) are both constructed-analog methods that are conceptually similar to LOCA. In both methods, the selection of the closest analog days is carried out with respect to the entire domain, rather than the LOCA method of selecting analogs at regional-then-local scales. The analog days are then combined by computing weights such that the weighted sum of the analog days best reproduces the GCM-modeled day's pattern being downscaled, rather than selecting a single best analog day as with LOCA. These same weights are then applied to the original fine-resolution observations from the analog days, producing the final spatially downscaled field. One drawback of BCCA and MACA is that as the domain size increases (e.g., to the contiguous U.S.), it becomes increasingly difficult to find close analog days for the entire

Climate Mapper



Link: https://climatetoolbox.org/tool/climate-mapper domain. Also, when downscaling precipitation, it becomes more likely that some of the analog days will have precipitation where the GCM model day has none, which will result in spurious rainfall for that day in the downscaled dataset. Finally, combining multiple analog days over a large domain tends to miss localized extreme precipitation events that occur on a single day, which can influence analyses of the impacts of projected extremes.

Delta method. The simplest statistical downscaling approach is the delta, or period change, method. The delta method starts with time series of historical daily or monthly climate data from gridded observations or from individual stations. The change in the monthly climatological average of temperature between a GCM simulated historical period and GCM projected future period is calculated across the GCM grid. These changes (deltas) are interpolated from the GCM grid down to the observation locations, and then added to the historical observations to produce the downscaled projections. Similarly, the monthly percent change in precipitation from the GCMs is applied to the precipitation observations. The delta method incorporates the coarse-scale patterns of climate change seen in the GCMs while preserving the fine-scale spatial detail and time sequences of weather events from the historical data.

The delta method can also be applied to data that has already been downscaled with another statistical or dynamical method, instead of raw GCM output. This downscaling-and-delta approach was used to generate the climate inputs to the hydrologic models used in the Colorado River Water Availability Study (CWCB 2012) and the Front Range Climate Change Vulnerability Study (Woodbury et al. 2012). The choice of the delta method in these studies indicated a preference for the already observed climate sequences (offset by the GCM-derived deltas) over the future climate sequences that are simulated by the GCMs. The historical sequences are certainly more familiar to stakeholders but cannot capture future changes in climate variability.

Dynamical methods

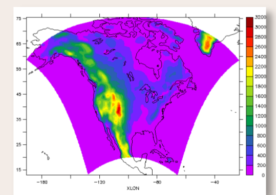
As with statistical methods, dynamical approaches to regional climate projection have been evolving for over 20 years (Giorgi and Mearns 1991; Leung, Kuo, and Tribbia 2006; Mearns et al. 2013). The general class of models primarily used in dynamical downscaling is referred to as Regional Climate Models (RCMs). RCMs are atmospheric models that run at higher resolutions than GCMs (typically 20–50 km), over a limited domain (i.e., not global). An RCM uses the 3-dimensional atmospheric output from a GCM to supply the conditions at the boundary of the RCM's domain. The RCM then simulates the interior of its domain using fluid dynamics and other equations and physical parameterizations, much like a GCM. One benefit of dynamical downscaling methods is that they involve fewer assumptions that may become inappropriate in a future climate, such as the assumption, inherent in statistical downscaling, that the historical spatial relationships in climate will not change. But there are still assumptions of climate stationarity embedded in the parameterizations and calibration of RCMs.

Large Regional Domain (NARCCAP and NA-CORDEX). The traditional use of RCMs centers on the idea that an RCM should cover a sufficiently large domain that regional-scale circulation changes are represented, e.g., the North American Monsoon, and that such models should be driven directly with the circulation fields from a GCM to permit changes to regional circulation and weather patterns to be directly represented. This approach was used in the North American Regional Climate Change Assessment Program (NARCCAP; Mearns et al. 2013) and the North American Coordinated Regional Downscaling Experiment (NA-CORDEX; Mearns et al. 2017).

Both NARCCAP and NA-CORDEX employed multiple RCMs to downscale multiple GCMs, with the objective of better understanding the uncertainty in regional climate stemming from both GCMs and RCMs. The NARCCAP RCMs used a grid spacing of approximately 50 km, while the NA-CORDEX RCMs used grid spacings of 50 km and 25 km. While these models provide a better representation of the large-scale regional climate patterns than GCMs, they are not at a sufficient resolution for hydrologic impact assessments in the Colorado River Basin and would require additional statistical bias correction and downscaling. In addition, due to the computational cost of RCMs, these simulations have been performed for many fewer GCMs than in the primary statistical downscaling datasets. NA-CORDEX has downscaled only six GCMs, primarily for the RCP 8.5 scenario. Only three GCMs have been downscaled for RCP 4.5 and only one of those RCM simulations was performed with the higher resolution 25 km grid.

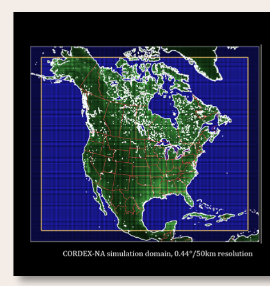
High-resolution convection-permitting and pseudo-global warming (PGW). In addition to the large-domain simulations, very high resolution simulations have been performed for shorter time periods. When atmospheric models use a grid spacing less than about 6 km, they can explicitly model convective processes, without the use of a simplified parameterization. In addition, they represent topography much better. Consequently, these high-resolution models better match observed precipitation and temperature patterns over the Upper Basin (Ikeda et al. 2010; Mahoney et al. 2013; Rasmussen et al. 2014) and over larger domains (Prein et al. 2015; Liu et al. 2017). However, since the computational cost of a model increases with the cube of the decrease in grid spacing, these high-resolution models have an enormous computational cost. Simulations over the contiguous United States using a 4-km grid spacing have been performed, but only over relatively short time periods: 13 years for the historical period and 13 years for the future period (Liu et al. 2017).

North American Regional Climate Change Assessment Program (NARCCAP)



Link: https://www.narccap.ucar.edu/

North American CORDEX Program (NA-CORDEX)



Link: https://na-cordex.org/

Because climate variability's short (decadal) time scales make it hard to discern the forced anthropogenic climate signal, these high-resolution simulations use a different method to evaluate the impacts of climate change, referred to as the Pseudo-Global Warming (PGW) method. The PGW method keeps the weather at the boundaries of the model consistent in current and future climate, but it perturbs those weather patterns with a mean climate change signal in the future climate. This means that these simulations have a warmer, moister background state, and they project what would happen to today's weather in a future climate. As a result, one can look at the differences between two 13-year simulations (current and future) to understand a climate change signal that would otherwise be obtained by comparing two 30-year periods from multiple GCMs, as is typically done. These simulations provide important guidance about the likely mean future climate changes driven by thermodynamic changes to the atmosphere, but they cannot depict climate changes caused by major shifts in weather patterns, such as the location of the storm track over the basin or the frequency of major storms.

Other regional climate downscaling approaches

Alternative approaches have been developed to investigate regional changes that fall somewhere in between the two main categories of downscaling methods, blending aspects of both. These include statistical downscaling methods based on atmospheric drivers and quasi-dynamical methods based on physical understanding.

Statistical methods based on atmospheric circulation indices (Wilby, Dawson, and Barrow 2002; Langousis and Kaleris 2014; Timm, Giambelluca, and Diaz 2015) have the advantage of being both developed to match regional observations (as with other statistical methods), and using output fields from a GCM that might reasonably be expected to be simulated well, such as upper air wind speed, temperature, and humidity. However, the relationships between these upper atmosphere parameters and hydrologically relevant meteorology, e.g., precipitation, are often highly non-linear and not well represented by purely statistical models. In addition, the atmospheric fields used do not have significant spatial variability, and as a result the predicted spatial variability in precipitation, in particular, is often too small and this results in unrealistic hydrologic behavior (Gutmann et al. 2014; Mizukami et al. 2016). Ensemble Generalized Analog Regression Downscaling (En-GARD) is a new statistical method, based on a combination of concepts and techniques (Wilby, Dawson, and Barrow 2002; Clark et al. 2004; Clark and Slater 2006), that aims to provide both realistic spatial patterns of precipitation and linkages to atmospheric variables that are better simulated in the GCM than precipitation.

Quasi-dynamical methods (Georgakakos et al. 2012; Gutmann et al. 2016) solve many of the same equations as full dynamical methods, but make various simplifications to permit them to run hundreds of times faster than traditional RCMs. For example, the development of the Intermediate Complexity Atmospheric Research model (ICAR; Gutmann et al. 2016) makes use of an analytical approximation to represent the wind field over mountain ranges, and then performs the same physical advection of heat and moisture in a high-resolution domain while using physical parameterizations from the Weather Research and Forecasting model (WRF; Skamarock and Klemp 2008) to model precipitation and the near-surface air temperature. These quasi-dynamical methods are likely to be useful for predicting changes in orographic precipitation and even land surface feedbacks in the Colorado River Basin. Large ensembles of climate projections from these methods are only just now being produced.

Currently, Gutmann and collaborators at NCAR are conducting a study in which they are applying En-GARD and ICAR to CMIP5 projections to produce GCM-informed Colorado River Basin streamflow ensembles, in order to evaluate the results and understand the implications of using these downscaling methods. This work is being funded by Reclamation and the other sponsors of this report.

Uncertainties and knowledge gaps in regional climate downscaling

Regional climate downscaling has many uncertainties associated with it. In particular, any regional climate method is reliant on information from the GCM, to varying degrees, and a regional climate projection can only compensate for some aspects of GCM performance deficiencies (Maraun et al. 2017). In addition, a large number of physical processes known to operate on smaller scales, such as the snow-albedo feedback effect (Letcher and Minder 2015) are not represented in statistical methods and can be clearly demonstrated to alter the climate change signal (Lanzante et al. 2018). Similarly, orographic precipitation is not well represented in GCMs, and it is not clear that statistical methods can meaningfully quantify a precipitation change signal when the underlying GCM simulation is improperly specifying how precipitation is being produced.

In general, dynamical and quasi-dynamical methods are better able to explicitly represent features such as the changing distribution of precipitation over a mountain range as snow changes to rain. However, these physically explicit models require numerous parameters within them, which are themselves uncertain. How fast does a snowflake melt as it falls? How does sub-grid variability in the land surface influence local air temperature?

Other GCM deficiencies may lead to poor regional climate signals, regardless of the downscaling method. In particular, no regional climate method is able to fully correct for GCM errors in the location of the primary mid-latitude storm track, such as over the western U.S., and the resulting errors in the frequency of storm systems for the region. While some large-domain RCMs may be able to shift the storm track location internally, they are somewhat constrained at the domain boundaries by the GCM conditions that drive the RCM. Of greater concern, if the GCM storm track is in the wrong location, statistical methods can correct the effect of this shift with respect to the historical climate record, but they are not addressing the root cause. If the GCM then predicts a future shift in this incorrectly positioned storm track, then a statistical method may inherit from the GCM a change in precipitation of a different sign than if the actual, correctly located, storm track had shifted in the same way (Maraun et al. 2017). As a result, GCMs should first be evaluated for the large-scale circulation that matters to a given region and application before attempting further regional climate refinements.

Opportunities for improvement

There are three overlapping areas for improving our regional understanding and quantification of the future climate change signal in the Colorado River Basin. The first would be further development and deployment of physically oriented methods for studying and projecting regional climate, whether dynamical, statistical, or hybrid (e.g., ICAR, En-GARD, NA-CORDEX, WRF). Most statistical downscaling methods are perfectly adequate at producing fine-scale climate projections to use as inputs to hydrology models, but they can't add to our understanding of physical processes. Second, clear metrics are needed to evaluate the validity of the future climate change signal predicted by different methods. While multi-decadal future projections cannot be validated against observations in the same manner as weather forecasts, there are ways to assess whether one method produces more physically realistic and plausible climate changes than another. Third, better understanding of what is required for a GCM projection or downscaled regional projection to be meaningful in the basin is needed; if the GCM-simulated historic storm track is shifted far from its actual location, it is likely that neither the GCM simulation nor a downscaled regional projection based on it can be trusted to provide changes in cool-season precipitation for the basin. We also need to identify which aspects of future regional climate changes are more or less predictable, and emphasize the former in vulnerability assessment and planning, and conversely, deemphasize the latter.

11.6 Projected future climate changes for the basin

As noted previously, most of the pertinent spatial and temporal information seen in downscaled GCM output is inherited from the "parent" GCM and is not the result of the downscaling method. While GCMs do struggle with many regional to local-scale details, they do a reasonable job in capturing the important physical phenomena of the climate system that play out between global and regional scales. By looking at the direct-from-GCM projections first, one can also better discern in what ways the regional projections from different downscaling methods may differ from the underlying GCM simulations.

The sections below look at projected climate *changes*, referring to the differences in the GCM's projections of a variable (temperature or precipitation) between a historical period and a future period.

Projected temperature change (direct from GCMs)

All of the CMIP3 and CMIP5 climate models, under all emissions scenarios, project that the climate of the Colorado River Basin will continue to rapidly warm relative to historical variability. Projected changes in temperature for the western U.S. by the mid-21st century (2041–2070) from CMIP5 climate models under two emissions scenarios (RCP 4.5 and RCP 8.5) are shown in Figure 11.6.

Model ensembles under RCP 8.5 (high emissions scenario) show generally warmer outcomes than under RCP 4.5 (medium-low emissions scenario) due to the higher levels of greenhouse gases and the associated climate forcing. However, within each emissions scenario, the 30+ projections (one from each GCM) differ in the projected magnitude of future warming, and so the respective ranges of the projected warming under the two scenarios overlap considerably. Under RCP 4.5, the basin's annual temperatures are projected to warm by +2.5°F to +5°F by mid-century compared to the late 20th century average. Under RCP 8.5, the basin's annual temperatures are projected to warm by +3.5°F to +6.5°F by mid-century. The projected warming in the warmest 20% of the projections under RCP 4.5 is similar to the median projection under RCP 8.5. Most of the projections under RCP 4.5, and nearly all of the projections under RCP 8.5, show a mid-century climate that is, on average, at least 3°F warmer than the 1971–2000 baseline and thus as warm as or warmer than the warmest individual years in the historical record.

The differences in warming shown by the various projections under each RCP have two primary sources; the first and more important is that the GCMs have different simulated responses to each increment of greenhouse gases (i.e., forced change), and the second is the "noise" of simulated multi-decadal natural (internal) variability in temperature—which, while relatively smaller than the forced change, is still present.

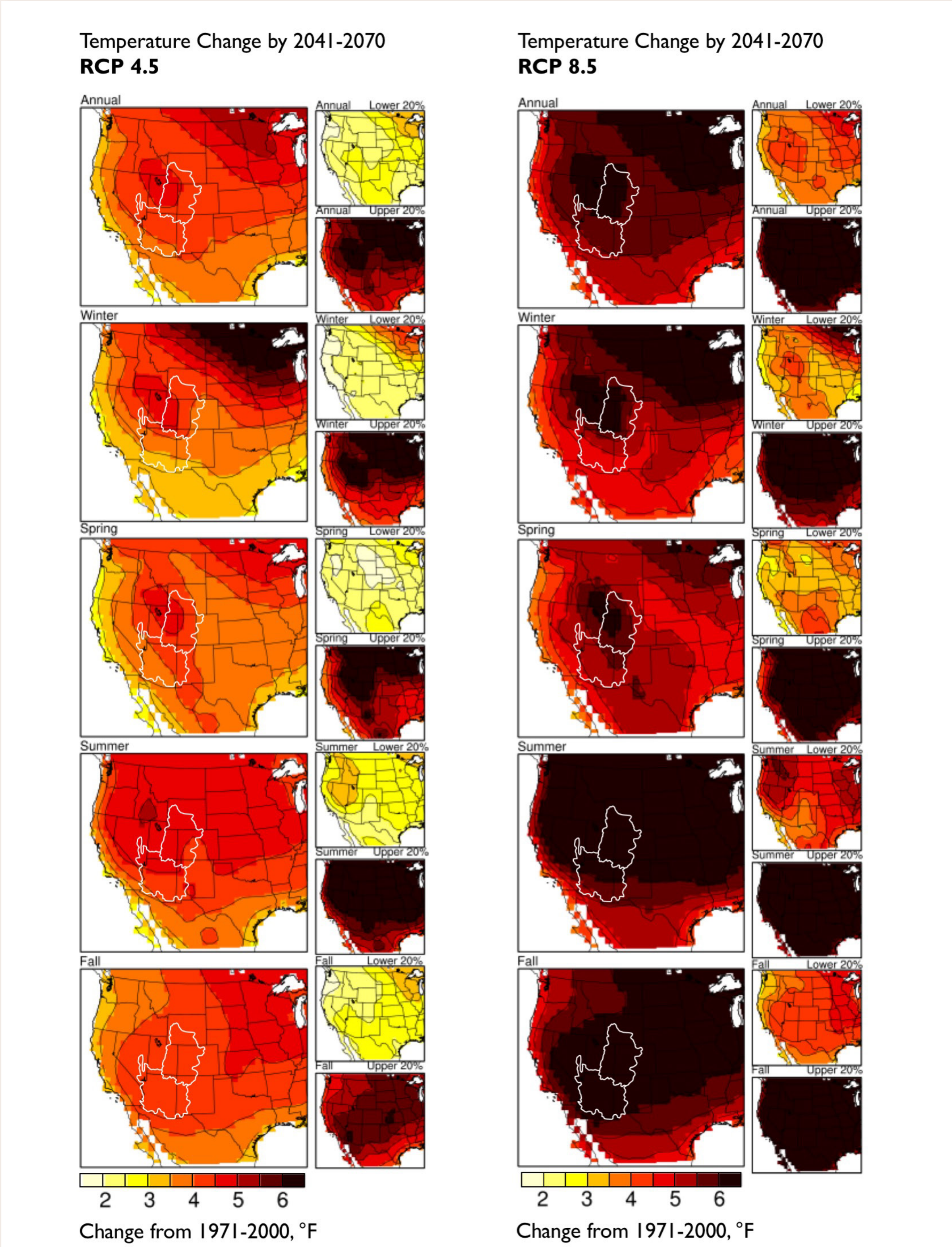


Figure 11.6

Projected annual and seasonal temperature changes by 2041–2070 over the western U.S. from an ensemble of GCMs under RCP 4.5 (left) and RCP 8.5 (right). The large maps show the average change across all of the projections for that RCP (n=37; one projection per GCM), and the smaller maps show the averages of the coolest 20% (n=8) and warmest 20% (n=8) of the projections. (Source: adapted from Lukas et al. 2014. Data: CMIP5 projections re-gridded to 1-degree grid (not downscaled); http://gdo-dcp.ucllnl.org/)

Additional features of the projected temperature changes are seen in Figure 11.6. Warming is expected to be slightly greater in summer than the other seasons due to land surface feedbacks; once soils dry out in summer, the energy that had been evaporating soil moisture can instead warm the land surface and the air. The warming is expected to be slightly greater in the Upper Basin compared with the Lower Basin, due to the Upper Basin's greater distance from the oceans' moderation of temperature changes; in fact, the Upper Basin is partly within the "bullseye" of the largest projected warming in the contiguous U.S., which is centered on the northern Great Basin.

Projected precipitation change (direct from GCMs)

The GCMs are in general agreement in projecting a north-south gradient in precipitation change across the western U.S., in which the northern tier of states is expected to see an increase in annual precipitation, and the Southwest is expected to see a decrease in annual precipitation. The Upper Basin sits in the transition area between these two regions, and while the uncertainty about the magnitude of precipitation change is no larger than for other parts of the U.S., there is more uncertainty about the *direction* of change, since the average of the models sits closer to the zero-change line.

Projections of annual and seasonal precipitation change from CMIP5 models under RCP 4.5 and RCP 8.5 are shown in Figure 11.7. On average, the GCMs indicate slight overall tendencies toward higher annual precipitation in the Upper Basin and toward lower annual precipitation in the Lower Basin under both RCP 4.5 and RCP 8.5. Those tendencies are enhanced for the northern half of the Upper Basin (wetter) and the southern half of the Lower Basin (drier). For the Upper Basin, the "wetter" projections call for around 5–10% more annual precipitation, while the "drier" projections call for 5–10% less precipitation. For the Lower Basin, the wetter projections call for 0–5% more annual precipitation, while the drier projections call for 10–15% less precipitation.

The north-south pattern in projected precipitation change across the basin and the West mainly arises because of two mechanisms: the first, *thermodynamic* (i.e., changes in energy states and flows) causes a general global increase in water vapor because the warmer atmosphere is able to hold more moisture (Seager, Naik, and Vecchi 2010). The second, *dynamic* (i.e., changes in atmospheric motions) is a northward shift in the average cool-season storm track across western North America as global atmospheric circulation changes in response to warming, resulting in an expansion of the relatively dry subtropical high-pressure zone that dominates Lower Basin climate (McAfee, Russell, and Goodman 2011; Seager, Naik, and Vecchi 2010).

In the northern tier of the western U.S., where the number of storm systems is projected to remain the same or increase, the increased water vapor leads to greater precipitation; in the far Southwest, the number of such systems is projected to decrease, canceling out the water vapor increase and leading to reduced annual precipitation (USGCRP 2017; McAfee, Russell, and Goodman 2011). The climate models disagree regarding the extent of the northward shift in storm tracks; this disagreement in part leads to their different depictions of future annual precipitation change for the basin, especially the Upper Basin, and other parts of the interior West.

Much of the uncertainty regarding whether annual precipitation will increase or decrease in the Upper Basin reflects inadequate scientific understanding of the expansion of the subtropical dry zone and the net effect of its interaction with the overall wetting of the atmosphere. There is also uncertainty about how ENSO may change in a dramatically warmed climate; greater future tendencies toward El Niño or La Niña would impart additional nudges to the average storm tracks and precipitation patterns.

The GCMs show more pronounced tendencies for change in seasonal precipitation for the basin than annual precipitation (Figure 11.7). In winter (DJF), most models show increased precipitation over the Upper Basin. In spring (MAM), most models show decreased precipitation for the Lower Basin. In summer, while the average change for precipitation for both the Upper and Lower Basins is not large, the "dry" projections show especially large decreases in summer precipitation. However, since the North American Monsoon is not represented well in the GCMs, and the convective storms that dominate summer precipitation cannot be directly simulated by the GCMs, the confidence in the projected changes in summer precipitation is lower than for the other seasons.

The differences in the precipitation change shown by the various projections under each RCP have two primary sources; the first and more important is that the GCMs have different simulated responses to each increment of greenhouse gases (i.e., forced change), and the second is the "noise" of simulated multi-decadal natural (internal) variability in precipitation.

Also important to hydrology and water management is that most of the GCMs project that the variability in precipitation will increase at all time scales over the western U.S., including greater interannual variability (Lukas et al. 2014; Pendergrass et al. 2017). This would mean more frequent occurrence of both very dry and very wet years, and more frequent oscillations from very dry to very wet conditions, such as in 2018–2019, or the reverse, such as in 2011–2012.

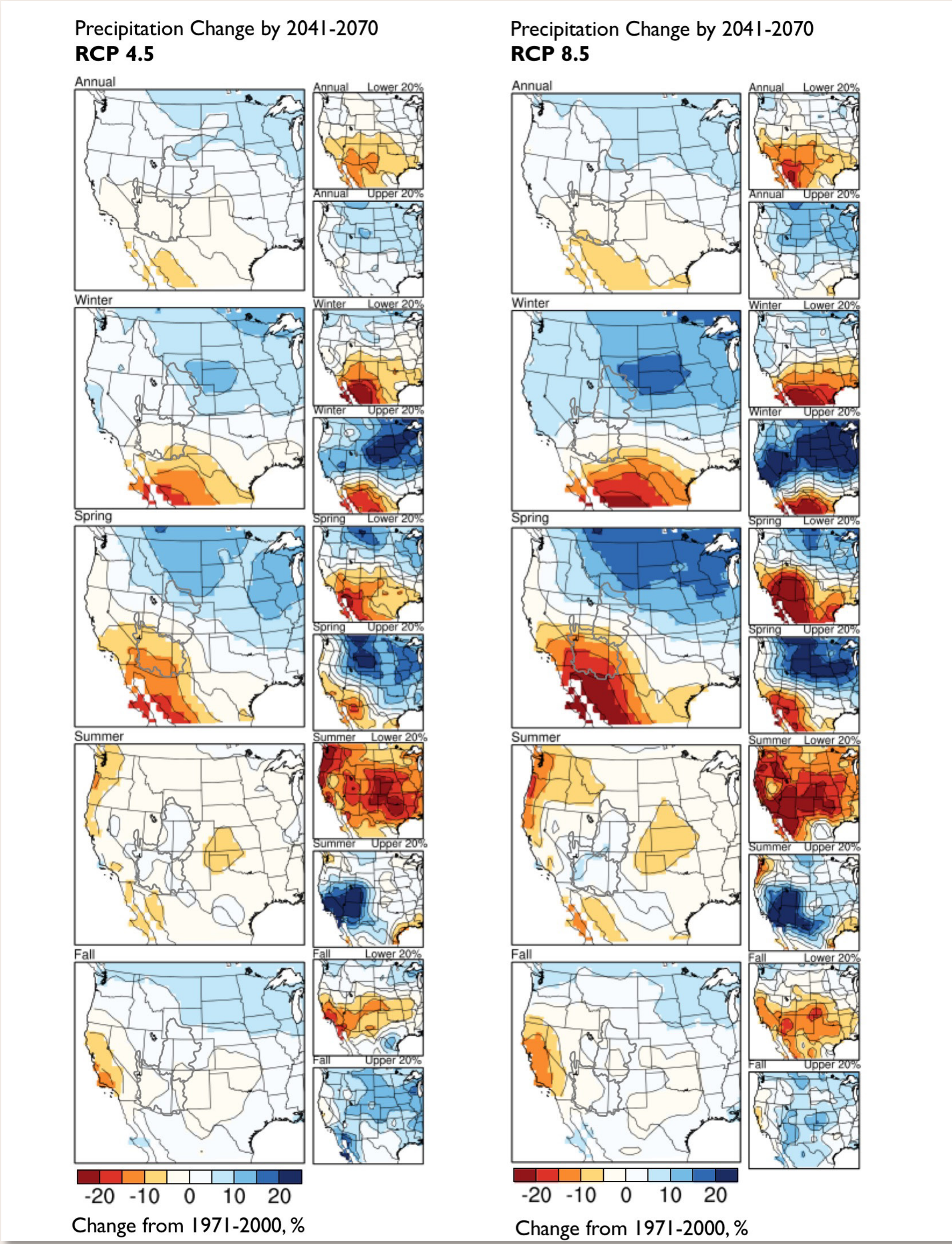


Figure 11.7

Projected annual and seasonal precipitation changes by 2041–2070 over the western U.S. from an ensemble of GCMs under RCP 4.5 (left) and RCP 8.5 (right). The large maps show the average change across all of the projections under that RCP (n=35; one projection per GCM), and the smaller maps show the averages of the driest 20% (n=8) and wettest 20% (n=8) of the model simulations. (Source: adapted from Lukas et al. 2014; Data: CMIP5 projections re-gridded to 1-degree (not downscaled); http://gdo-dcp.ucllnl.org/)

The influence of downscaling methods on GCM climate projections

The GCM output is known to have deficiencies that downscaling is intended to correct. As a downscaling method bias-corrects the GCM output and spatially distributes that signal to finer scale, it may alter the GCM's climate change signal, as expressed in future trends. However, the influence of common downscaling methods on the projections of climate change has seldom been systematically examined or quantified. In a review of bias-correction methods, Maraun (2016) asserts that current bias-correction approaches cannot correct GCM-projected trends in a physically plausible manner, and so bias-correction approaches that deliberately preserve the GCM signal should be deployed.

For the Colorado River Basin and the western U.S., a clear example of GCM-signal alteration arose with the monthly BCSD projections based on CMIP3 (e.g., Reclamation 2011; 2012e). The BCSD procedure effectively imparted a "wettening," so that the bias-corrected and downscaled BCSD data projected larger increases in precipitation than did the underlying GCM projections. When BCSD was later used to downscale the CMIP5 GCM output, this wettening effect was even larger and had a significant influence on the corresponding ensemble of projected hydrologic changes for the Upper Basin (Reclamation 2014; Lukas et al. 2014), as noted in Table 11.3 and in the accompanying text. Maurer and Pierce (2014) found that the BCSD wettening as shown in CMIP5 was in fact due to the quantile mapping (QM) bias-correction procedure within BCSD, and that QM tends to reduce the future trend when the projection has more variability than the observed data, and increase the trend when the model has less variability than the observed data—in other words, the trend alteration appears to be a statistical artifact of the QM procedure. Subsequent analyses of QM in Reclamation (2020) have affirmed the observation that the QM procedure alters projected trends in a manner that is not consistent with physical mechanisms.

Figure 11.8 shows the ensemble mean change in annual precipitation of 10 CMIP5 GCMs that have been downscaled by BCSD as in Reclamation (2014), and by LOCA—which by design does not alter the GCM change signal during bias correction, though it may do so during the spatial downscaling. BCSD shows wetter outcomes (darker blues) in the Upper Basin headwaters and less-dry outcomes (fainter red) in the Lower Basin headwaters than LOCA.

In one of the first comprehensive evaluations of its kind, Alder and Hostetler (2019) compared downscaled projections of temperature and precipitation for the western U.S. generated using 6 different statistical methods, including BCSD (two variants), BCCA, MACA (two variants), and LOCA. The downscaled projections were compared with each other and with the projections from the 14 parent CMIP5 GCMs. They found, first, the

GCM change signals—especially in precipitation—were altered by all of the downscaling methods, with the degree of alteration differing according to region, downscaling method, and the parent GCMs. They found that most of these alterations stemmed from the specific gridded climate dataset (see Chapter 4) used to bias-correct and spatially distribute the GCM output for a particular method (Table 11.3).

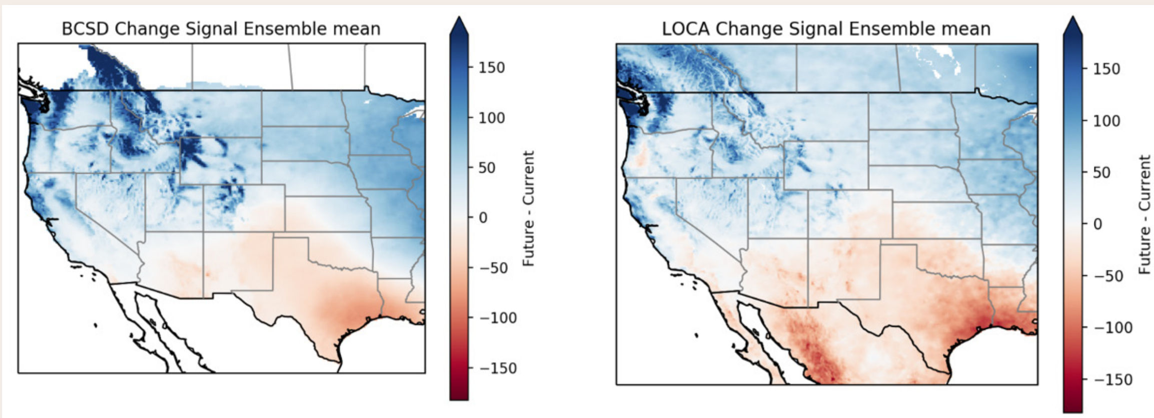


Figure 11.8

Projected percentage change in precipitation for the late 21st century (2070–2099 as averaged across the same set of 10 CMIP5 GCMs under RCP 8.5, using BCSD (left) and LOCA (right) procedures for bias-correction and spatial downscaling. Note that precipitation increases over the Upper Basin headwaters are larger (darker blues) for the BCSD projections. (Source: E. Gutmann, NCAR; Data: http://gdo-dcp.ucllnl.org/)

Figure 11.9, from Alder and Hostetler (2019), shows the projected changes in cold-season (October-April) temperature and precipitation for the Upper Basin from the individual 14 GCMs and ensemble of those GCMs, and from the 6 downscaling methods (by individual GCM and the ensemble). The alteration of the GCM cold-season temperature signal by the downscaling method is very small overall except in the case of BCCA, which imparts a clear cooling to the GCM change signal. For precipitation, all 6 downscaling methods impart some wettening to the GCM change signal; the wettening is smallest in MACA-L (MACAv2-Livneh) and in LOCA, while the wettening is largest in the two variants of BCSD.

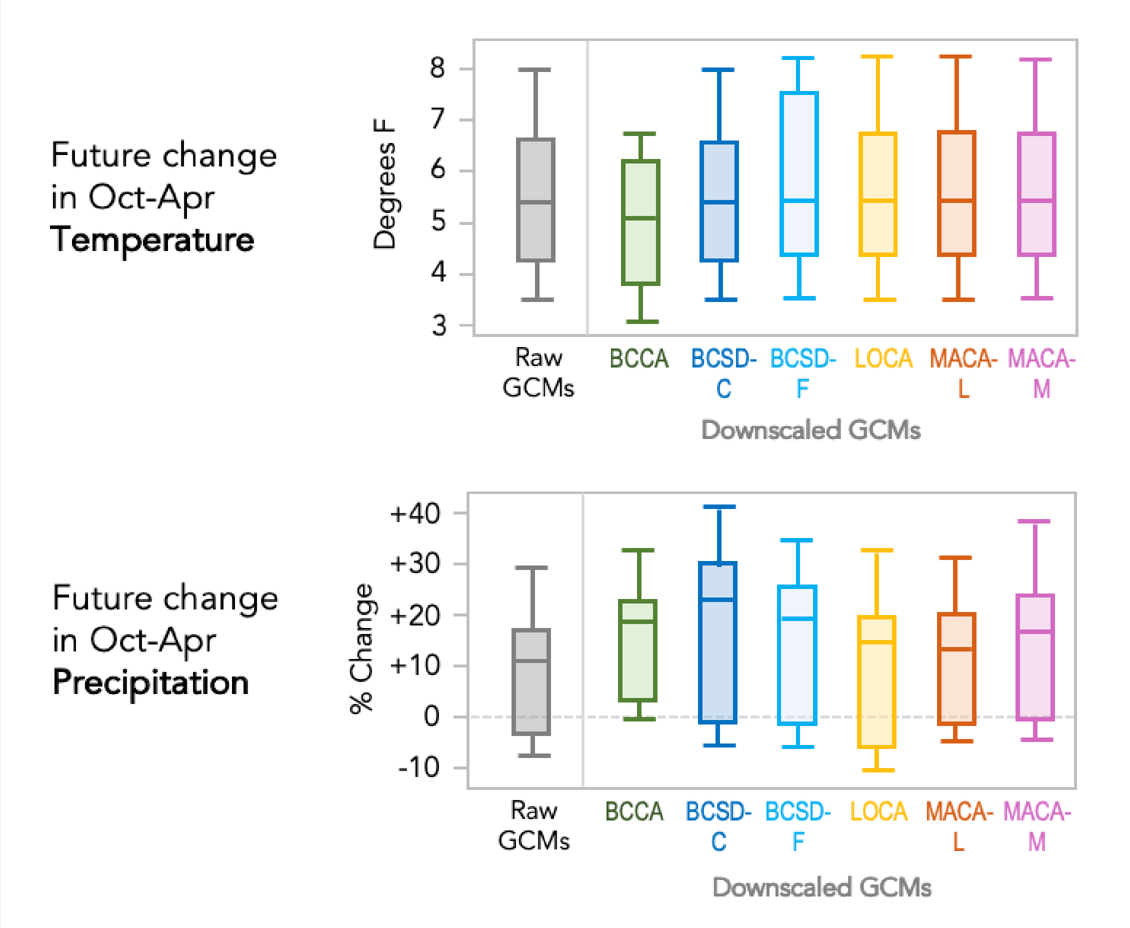


Figure 11.9

Future change (2075–2099 vs. 1950–1999) in average cold season (October–April) temperature (upper) and total precipitation (lower) for the Upper Colorado River Basin under RCP 8.5 shown by 14 "raw" GCM projections (gray) and the corresponding downscaled projections from six statistical downscaling methods (colors). BCSD-C = Reclamation variant of BCSD (Reclamation 2014); BCSD-F = NASA/USGS variant of BCSD (Thrasher et al. 2013); MACA-L = MACAv2-Livneh; MACA-M = MACAv2-METDATA. (Source: adapted from Figure 2 in Alder and Hostetler 2019)

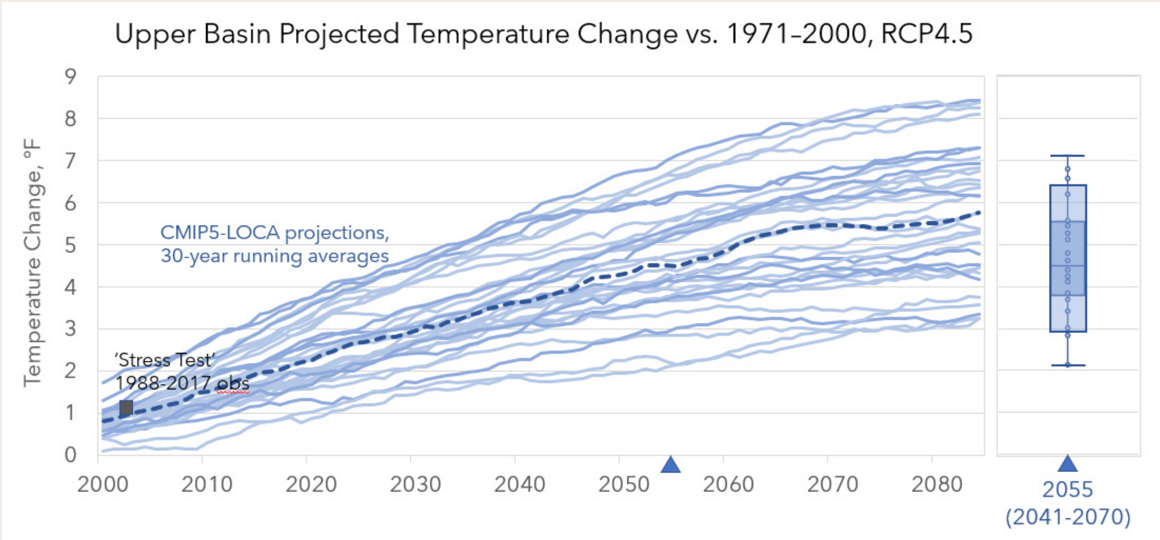
One should keep in mind that these signal alterations and differences between methods are still substantially smaller than the overall range of the GCM-projected changes without downscaling (the black boxplots in Figure 11.9). But they do add another uncertainty to the projections of climate change and hydrologic change for the basin. In most cases, we lack criteria to determine which method(s) and accompanying alterations are the most reliable. For now, users should be cognizant of the uncertainties related to downscaling methods, and researchers will continue to look for better ways to evaluate them, including whether some methods are better suited for some types of applications and their associated impact metrics (e.g., hydrologic, ecological) or for certain regions. Some of this applications knowledge has been gleaned by the research community, but it has not been systematically documented.

Projected Upper Basin temperature and precipitation change from a downscaled dataset

Given the discussion above, and recognizing the relative merits of the different available datasets of downscaled GCM data, selecting a representative dataset to examine in greater detail does not imply that it is the best dataset, either in general or for informing water management in the Colorado River Basin. Here the CMIP5-LOCA downscaled projection dataset has been chosen because it contains a broad sample of the full CMIP dataset (32 models, one projection each, under two emissions scenarios, RCP 4.5 and RCP 8.5), it lacks the precipitation 'wettening' effect seen in the BCSD datasets, and it is used as the basis for hydrology projections in the forthcoming CMIP5 report (Reclamation 2020) alongside CMIP5-BCSD data. The features of the temperature and precipitation projections that are highlighted below are held in common with nearly all of the statistically downscaled GCM datasets, and are not specific to LOCA.

Figure 11.10 shows the projected Upper Basin temperature change, compared to a 1971–2000 baseline, from CMIP5-LOCA dataset (32 models, one projection each) driven by the RCP 4.5 (top) and RCP 8.5 (bottom) emissions scenarios. A 30-year running average has been applied to the traces to match the typical 30-year analysis period for evaluating future change. To further place the projections in the context of the recent past, the average observed temperature anomaly over the 30-year period 1988–2017 (i.e., the 'Stress Test'; Chapter 9) is shown; the Upper Basin climate for that period was already 1.1°F warmer than the 1971–2000 baseline.

Just as in the raw GCM output shown earlier, all of the traces show a much warmer future climate, with the magnitude of warming depending on the emissions scenario (the RCP 4.5 and RCP 8.5 ensembles overlap but are clearly different overall), each model's climate sensitivity (as seen in the spread of the traces under each scenario), and how far out into the future one looks. In general, the projected warming shows a fairly linear response to the respective climate forcing in the emissions scenarios as shown in Figure 11.4; e.g., the RCP4.5 traces tend to flatten out after 2050, just as the forcing in the RCP 4.5 scenario does. Note that while there is some variability (e.g., "bumpiness") present in the traces, the traces by and large maintain their relative positions over time, indicating that the anthropogenic forced change in temperature is dominant compared to internal (natural) variability at a 30-year timescale.



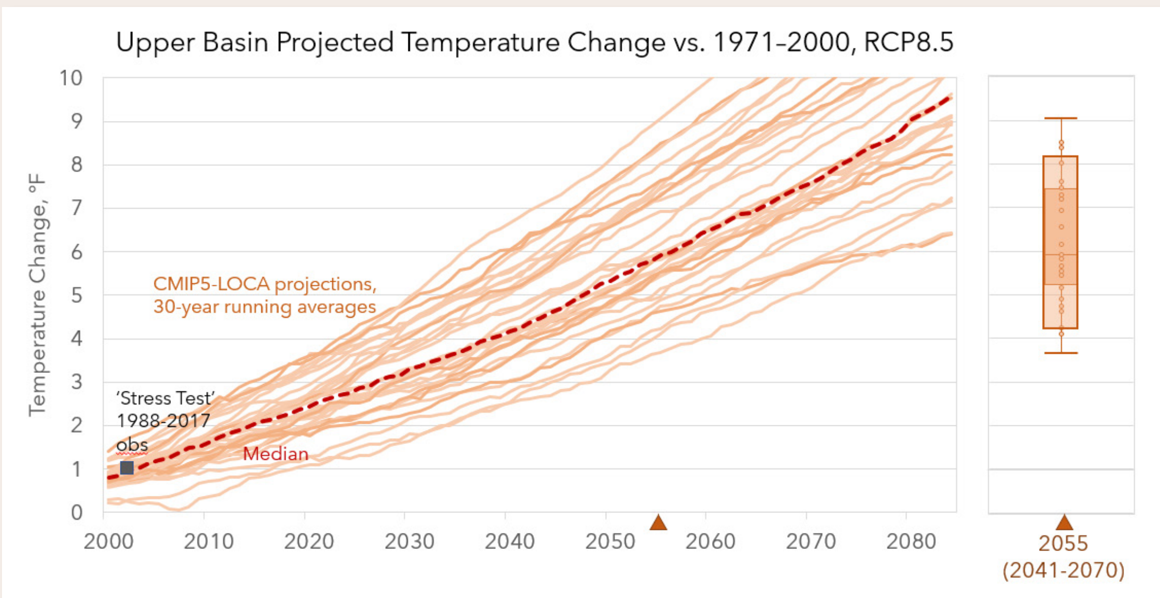
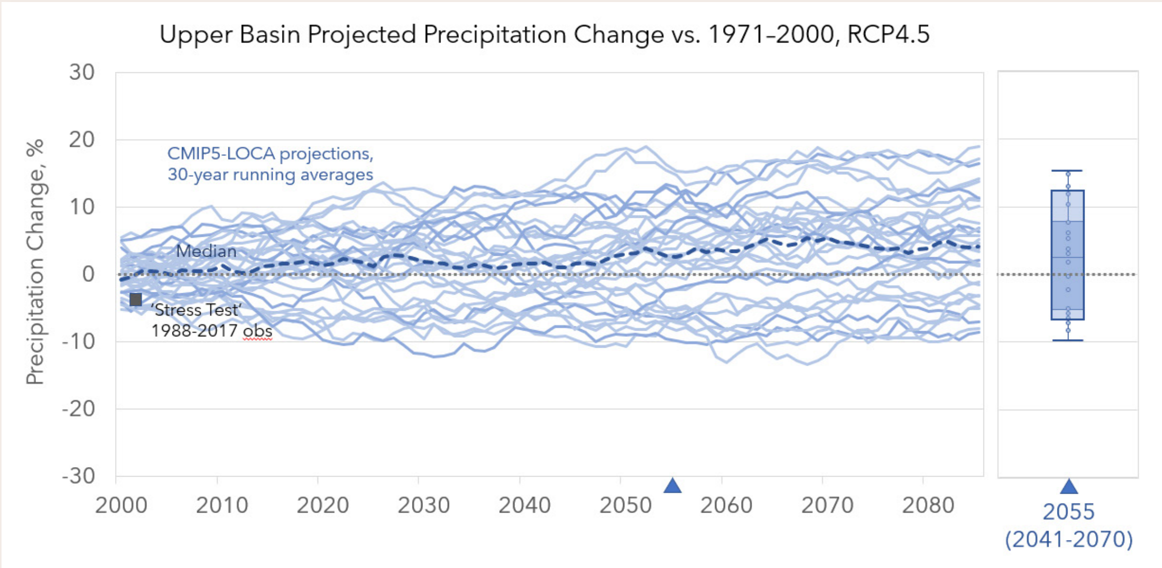


Figure 11.10

Projected future temperature change for the Upper Basin compared to a 1971–2000 baseline, from two ensembles of 32 CMIP5 projections under two emissions scenarios (top: RCP4.5; bottom: RCP8.5) downscaled with LOCA. The lighter traces on both time series plots are the 30-year running averages, plotted on the middle (15th) year, of the projected annual temperature anomaly, with the median trace shown as the dark dashed line. The 30-year average of the observed temperature ("obs") anomaly over the 1988–2017 'Stress Test" period is shown as a black square. The box-whiskers plots show the distribution of the 30-year average values at 2055 (2041–2070); the outer boxes show the 10th and 90th percentiles; the inner boxes show the 25th, 50th, and 75th percentiles, and the max/min are shown at the ends of the whiskers. (Data: D. Pierce, Scripps Institution; http://loca.ucsd.edu; Pierce, Cayan, and Thrasher 2014)



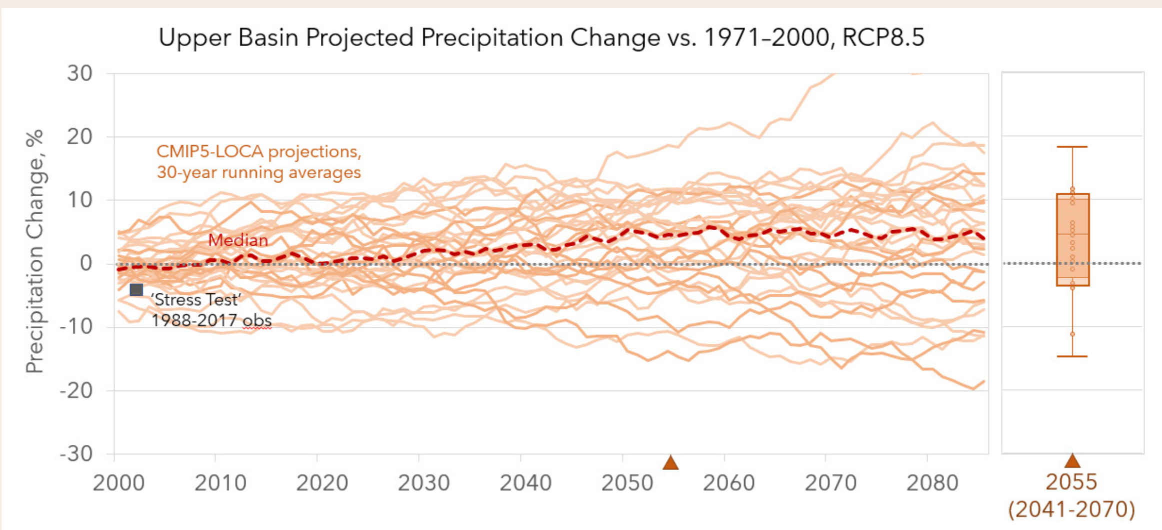


Figure 11.11

Projected future precipitation change for the Upper Basin compared to a 1971–2000 baseline, from two ensembles of 32 CMIP5 projections under two emissions scenarios (top: RCP4.5; bottom: RCP8.5) downscaled with LOCA. The lighter traces on both time-series plots are the 30-year running averages, plotted on the middle (15th) year, of the projected annual precipitation anomaly, with the median trace shown as the dark dashed line. The 30-year average of the observed precipitation ("obs") anomaly over the 1988–2017 'Stress Test" period is shown as a black square. The box-whiskers plots show the distribution of the 30-year average values at 2055 (2041–2070); the outer boxes show the 10th and 90th percentiles; the inner boxes show the 25th, 50th, and 75th percentiles, and the max/min are shown at the ends of the whiskers. (Data: D. Pierce, Scripps Institution; http://loca.ucsd.edu; Pierce, Cayan, and Thrasher 2014)

The magnitudes of projected warming for the 2041–2070 period centered on 2055 are essentially the same as those seen in the raw GCM data and depicted in Figure 11.6. As seen in the box-whiskers plots in Figure 11.10, under RCP 4.5, the vast majority of the projections show warming of +3.0° to +6.5°F by mid-century compared to the late 20th century average, and under RCP 8.5, the vast majority show warming of +4°F to +8°F. As discussed earlier, some climate analysts have suggested that the RCP 8.5 scenario should be de-emphasized due to unrealistic assumptions about future energy supply sources. But note that several of the higher-warming RCP 4.5 traces exceed the median RCP 8.5 level at 2055, and if traces from RCP 6.0 were available from the LOCA dataset, many of them would track at that level too. So even if the RCP 8.5 scenario itself is in fact "very unlikely," as Hausfather and Peters (2020) asserted, many of the warming outcomes associated with that scenario are also attainable under other RCPs for the same time period.

As discussed earlier in the context of the maps of the raw GCM precipitation output (Figure 11.7), the Upper Basin is located in the transition zone between areas of expected drying (lower annual precipitation) to its south, and expected wettening (higher annual precipitation) to its north. Figure 11.11 shows the projected Upper Basin precipitation change over the 21st century. The average observed precipitation anomaly (-3.5%) during the 30-year 'Stress Test' period (1988–2017) is also shown.

The LOCA downscaling procedure by design tries to preserve the GCM-projected trends, and as seen in Figure 11.9 it preserves the GCM's precipitation trends better than other downscaling methods. So the overall message of the CMIP5-LOCA projections in Figure 11.11 is very consistent with the raw GCM output from CMIP5: there are slight overall tendencies toward higher annual precipitation in the Upper Basin under both RCP 4.5 and RCP 8.5.

But also evident in the time-series plots of Figure 11.11 is a feature that was hidden in the change maps of Figure 11.7, but noted in the text: Multi-decadal internal (natural) variability strongly influences the precipitation traces, manifesting as frequent excursions in the 30-year averages, up and down by 5% or more. These excursions make it hard to discern the long-term trends that might be attributable to forced changes, e.g., changes in atmospheric circulation (ENSO, prevailing storm tracks) or the global moistening of the atmosphere in a warmer climate. To the extent those forced changes are present, they are not leading to significantly different overall changes under RCP 8.5 (which has greater climate forcing) than under RCP 4.5. The ensemble medians throughout the 21st century are very similar, though from 2050 onward the RCP 8.5 has greater spread across the ensemble, perhaps indicating that at least the outlying precipitation projections are showing greater influence of simulated changes in atmospheric circulation.

Toward the end of the next section, these same LOCA-downscaled projected temperature and precipitation changes will be shown again, after they have been integrated into simulations of future hydrology for the Upper Basin.

11.7 Projections of future Colorado River hydrology under climate change

The future warming projected by all climate models for the Colorado River Basin (Figures 11.6 and 11.10) by itself will have clear impacts on the hydrologic cycle. Most significantly, warming will tend to reduce annual runoff, given the same amount of precipitation. As detailed in previous sections, the magnitude of the warming for any given future period is uncertain, although the progressive nature of the warming means that a slower warming projection will, over more time, still reach thresholds that a faster warming projection reaches earlier. Precipitation, which is the primary determinant of the variability in annual runoff (see Chapter 2), has uncertainty regarding both the direction and magnitude of future change.

The sensitivity of basin runoff to a given temperature change, and to a lesser extent the sensitivity of runoff to a given precipitation change, are also uncertain (Vano, Das, and Lettenmaier 2012; Vano and Lettenmaier 2014; Vano et al. 2014). Together, these uncertainties regarding the magnitude of future temperature and precipitation change, and regarding the true sensitivity of basin hydrology to specific temperature and precipitation changes, have led to a broad range of potential future hydrologic outcomes. However, across the many studies and assessments of future basin hydrology, this range of outcomes is strongly tipped toward reduced runoff, reflecting the pervasive impact of the projected warming.

Methodologies used in past and recent studies

The earliest studies for the basin used empirical statistical relationships to translate basic climate change scenarios (e.g., + 2°C warming; -10% precipitation) into basin-scale hydrologic changes, and highlighted the importance of quantifying the sensitivity of runoff to both temperature and precipitation (Stockton and Boggess 1979; Revelle and Waggoner 1983). Later, Nash and Gleick (1991) set what has become a standard for most subsequent studies by deriving specific climate change factors directly from two GCMs and then using a hydrology model (Sac-SMA; Chapters 6 & 8) to translate those climate scenarios into runoff changes for select Upper Basin watersheds.

The modern era of runoff-modeling studies began with Christensen et al. (2004), who pioneered what has become the most prevalent approach (see Figure 11.1 and Table 11.1): a set of GCM projections is statistically downscaled, and the downscaled temperature and precipitation projections are run through a hydrologic model (in their case, and in most later cases, the VIC model; Chapter 6) to obtain future basin streamflows. This same general approach has been followed by many later studies (Table 11.4), with increasingly larger ensembles of GCM projections.

The first analyses of climate change-informed hydrologic simulations for the Colorado River Basin or its headwaters to be formally sponsored by water agencies and to be specific to their long-term water planning appeared in the early 2010s:

- Joint Front Range Climate Change Vulnerability Study (Woodbury et al. 2012)
- Colorado River Water Availability Study, Phase 1 (CWCB 2012)
- West-Wide Climate Risk Assessment (WWCRA; Reclamation 2011)
- Colorado River Basin Water Supply and Demand Study ('Basin Study;' Reclamation 2012e)

These studies exemplified the top-down approach to climate change impact assessment, in which an ensemble of hydrologic simulations is developed from GCMs in order to drive a water system model. All were based on the same set of downscaled GCM climate projections (CMIP3-BCSD), a dataset developed by a consortium including Reclamation and USACE, although the projections were processed differently in each study. The Basin Study (Reclamation 2012e) marked the first basin-scale planning study involving Reclamation that based analyses of future water vulnerability on climate change-informed hydrology. The process of conducting these four studies shed light on several of the key methodological considerations and uncertainties described below and their implications for projecting future changes in basin water supplies. The latter two studies used a larger ensemble of simulations (112 in both cases) that more completely captured the full range of future climatic and hydrologic conditions depicted across the CMIP3 GCMs.

Subsequent assessments have largely focused on updating and refining the ensemble of simulations, by using the next generation of climate models, culling lower-performing climate models, using newer downscaling approaches to assess regional changes, or using different hydrologic models. The update to WWCRA (Reclamation 2016b) used the same approach as the original, but with newer climate models (CMIP5) and a later version of the VIC hydrologic model. Similarly, the forthcoming report, "Exploring Climate and Hydrology Projections from the CMIP5 Archive" (Reclamation 2020) uses CMIP5 climate models, then screening of the models for performance, a primary downscaling method (BCSD), and also an alternate downscaling method (LOCA).

Results—future changes in annual Upper Basin runoff

Table 11.4 summarizes the results from about 20 studies and assessments since 2005 that have provided estimates of future changes in annual naturalized Upper Basin runoff and streamflow, in nearly all cases as measured at Lees Ferry. For a given methodology, the results from different studies have been similar, and thus the results across the studies are generalized in the "Synthesis of results" column. Looking across the different methodologies, there is broad consistency in two overall findings: 1) most individual simulations within a given study show reduced runoff for the mid-21st century, and 2) the mid-range of the simulations accordingly suggests a reduction in runoff of about 10% to 20%, i.e., down to an average of about 12.0–13.5 maf/year, compared to the historical hydrology of 14.8 maf/year. (There is one exception to these generalizations, as noted below.) Again, the overall tendency toward reduced runoff reflects the pervasive drying effect of the near-certain projected warming, which is either ameliorated by increased precipitation or exacerbated by decreased precipitation, depending on the particular simulation.

Table 11.4

Summary of results from studies since 2005 that have provided estimates of future changes in naturalized Upper Basin runoff. The studies are grouped according to methodology/primary GCM data. Previous summaries of the studies projecting future hydrology for the Upper Basin can be found in Ray et al. (2008); Lukas et al. (2014); and Vano et al. (2014)

Methodology	Studies or assessments using these simulations	Synthesis of results of these studies for Upper Basin runoff in mid-21st century	Comments
CMIP3 GCM projections + BCSD statistical downscaling + hydrologic model	Christensen and Lettenmaier (2007); Reclamation (2011); Woodbury et al. (2012); CWCB (2012); Reclamation (2012e); Harding, Wood, and Prairie (2012); Ficklin, Stewart, and Maurer (2013)	Most (60–80%) simulations show reduced runoff; median change -10% (-25% to +10%)	All studies used the VIC model except Woodbury et al. (Sac-SMA and WEAP)
CMIP3 GCM projections + delta method downscaling + hydrologic model	Deems et al. (2013)	Median change -10% to -20%	Individual simulations not reported; study also examined effects of dust on snow

Methodology	Studies or assessments using these simulations	Synthesis of results of these studies for Upper Basin runoff in mid-21st century	Comments
CMIP3 GCM projections + dynamical downscaling with RCMs; runoff directly from the RCMs	Gao et al. (2011)	Most (2 of 3) simulations show reduced runoff; changes -16% to +5%	Very small projection ensemble; study domain includes Lower Basin headwaters
CMIP3 GCM projections; runoff directly from the GCMs	Milly, Dunne, and Vecchia (2005); Seager et al. (2007)	Nearly all (~95%) simulations show reduced runoff; median change -10% to -20%	This method is less reliable for basin-scale runoff than other methods
CMIP5 GCM projections + BCSD statistical downscaling + hydrologic model	Reclamation (2016b; 2020)	About half of simulations show reduced runoff; median change 0% (-25% to +20%)	Outcomes are shifted wetter than other methods due to the BCSD bias-correction procedure's effects on precipitation
CMIP5 GCM projections + other statistical downscaling + hydrologic model	Alder and Hostetler (2015); Reclamation (2020)	Most (~70%) of simulations show reduced runoff; median change -5 to -10% (-25% to +10%)	Alder and Hostetler (2015) used a variant of BCSD lacking the procedure that leads to wettening; Reclamation (2020) used LOCA
CMIP5 GCM projections + observed runoff sensitivities to temperature and precipitation	Lehner et al. (2019)	All simulations show reduced runoff; median change -17% (-31% to -3%)	Future time period varies by GCM and corresponds to temperature increase of 2°C vs. 1950-2008
CMIP5 GCM projections; runoff changes directly from the GCMs	Seager et al. (2013)	Most (~80%) of simulations show reduced runoff; median change -10% (-30% to +10%)	Results are for the 2021-2040 period; for mid-century, the reductions would be more prevalent and larger
Generalized temperature change from GCMs + hydrologic models (or runoff sensitivity to temperature derived from hydrologic models)	McCabe and Wolock (2007); Udall and Overpeck (2017); Milly and Dunne (2020); Reclamation (2020)	All simulations show reduced runoff; median change -20% (-40% to -5%)	Results only reflect future changes in temperature, not changes in precipitation

There are some appreciable differences in the results among the respective methodologies. The most prominent is that the *CMIP5 + BCSD downscaling + hydrologic model* ensemble reported in recent Reclamation-funded studies (Reclamation 2014; 2016b; 2020) showed wetter (i.e., less dry) outcomes than earlier CMIP3-based hydrologies and CMIP5-based hydrologies produced using different bias-correction and downscaling methods (Alder and Hostetler 2019; Reclamation 2020).

Also, the studies that have analyzed Upper Basin *runoff output directly from GCMs*, whether based on CMIP3 or CMIP5, have found the future runoff reductions to be more prevalent and larger than studies using downscaled climate and hydrology. This shift toward drier outcomes is in part a consequence of the simplified topography in the GCM leading to a smaller or non-existent mountain snowpack.

The last methodology listed (*Generalized temperature change from GCMs + hydrologic model*) shows drier outcomes than other methods, because it only reflects the projected temperature change, and not the precipitation change. Udall and Overpeck (2017), like McCabe and Wolock (2007) a decade previously, argue for separating the impacts on runoff of temperature projections, in which we have very high confidence, from those associated with the much lower-confidence projections of future precipitation.

Finally, the Lehner et al. (2019) study used a novel methodology in which the temperature *and* precipitation changes from CMIP5 GCMs were combined with the respective sensitivities of runoff to temperature and precipitation as statistically derived from observations, creating "observationally constrained" projections of future runoff. All of the individual projections in Lehner et al. (2019) show reductions in streamflow, with magnitudes similar to the temperature-change-only runoff projections in Udall and Overpeck (2017) and similar studies.

Those studies that also include analyses at the sub-basin level consistently indicate a stronger tendency toward decreased runoff for the southern parts of the Upper Basin, including the San Juan River, and less so in the northern parts, including the upper Green River and the Yampa River (Reclamation 2012e; CWCB 2012; Alder and Hostetler 2015; Reclamation 2016a; 2020). This north-south gradient in streamflow outcomes is mainly driven by the corresponding north-south gradient in projected annual precipitation, since the projected magnitudes of warming for the different sub-basins are comparable.

As with the downscaled climate datasets, it is difficult to select one representative dataset from the many different analyses of future Upper Basin streamflows to examine in greater detail. Here, a CMIP5-LOCA-VIC dataset of projected streamflows is shown because it matches the CMIP5-

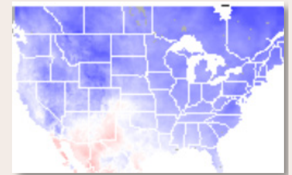
LOCA projections of Upper Basin temperature and precipitation discussed in the previous section, and because a very similar dataset was used in analyses in the forthcoming CMIP5 report (Reclamation 2020). (Note: The LOCA-based projected streamflows shown here in Figures 11.12 and 11.13 are not the same as the LOCA-based projected streamflows that will be available later this year on the [collaborative downscaled climate and hydrology projection archive](https://gdo-dcp.ucllnl.org/) hosted on Lawrence Livermore National Laboratory's Green Data Oasis; the latter dataset was processed using a different streamflow routing scheme and will have more individual projections.)

Figure 11.12 shows the projected streamflow change at Lees Ferry from CMIP5-LOCA dataset (32 models, one projection each) driven by the RCP4.5 (top) and RCP8.5 (bottom) emissions scenarios. A 30-year running average has been applied to the traces to match the typical 30-year analysis period for evaluating future change. Note that even with this 30-year smoothing, the individual traces show substantial variability, depicting swings in the apparent future change over the course of the 21st century. Nearly all of this variability is driven by the internal (i.e., natural) variability in precipitation, as shown in Figure 11.11. (See also the sidebar on natural variability below.) This means that the precise features of the distribution of the ensemble at any slice in time, e.g., the box-whiskers plots for 2055, are somewhat arbitrary in that they reflect a snapshot of ever-shifting multi-decadal variability as well as the forced anthropogenic change.

Also note that while the median change is negative (i.e. decreasing streamflow) throughout the 21st century under both RCP4.5 and RCP8.5, and many of the individual traces show streamflow decreasing by 10% or more, the ensemble medians remain relatively constant after about 2050 despite increasing projected basin temperatures. This is because the precipitation increases projected by most of the CMIP5 projections, while relatively small in percentage terms, are still large enough to compensate for the progressive effects of warming in about one-third of the streamflow traces. Even so, about 30% of the traces under both RCP4.5 and RCP8.5 show 30-year average flows at 2055 that are less than the average observed streamflow of 13.3 maf (13% below the 1971-2000 average) during the 1988-2017 period used as the "Stress Test" hydrology (Chapter 9).

Downscaled CMIP3 and CMIP5

Climate and Hydrology Projections



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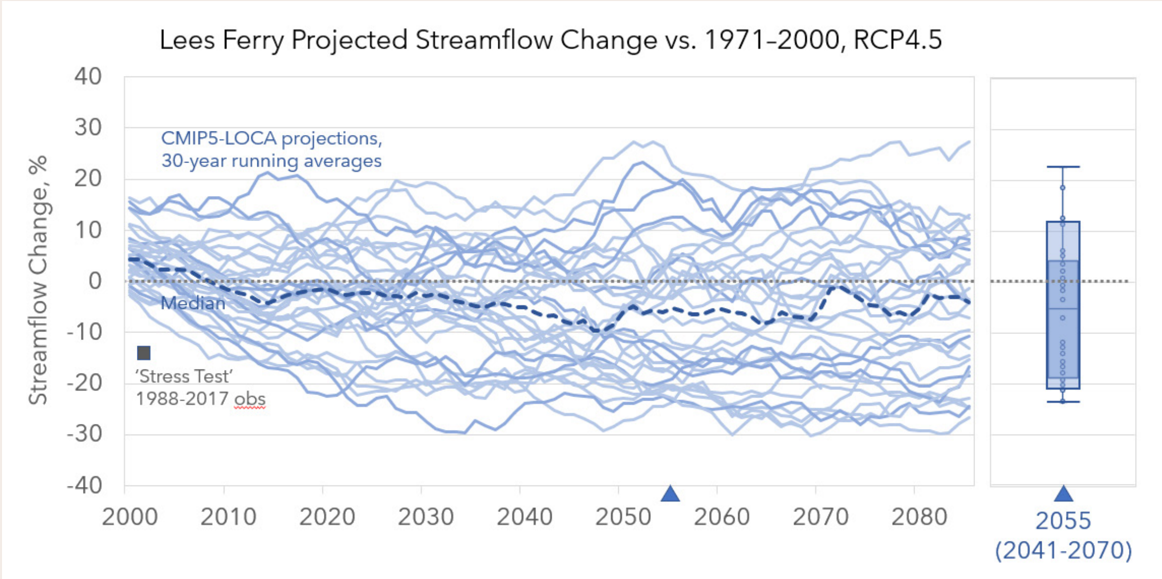

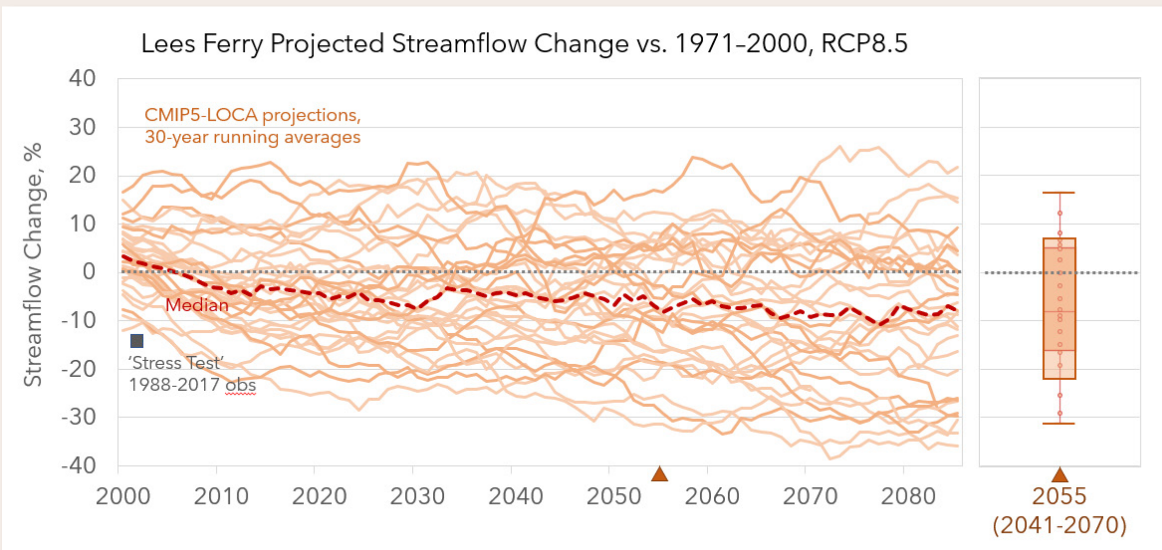

Figure 11.12

Projected future streamflow change at Lees Ferry compared to the 1971–2000 baseline, from two ensembles of 32 CMIP5 projections under two emissions scenarios (top: RCP4.5; bottom: RCP8.5) downscaled with LOCA and run through the VIC model to simulate hydrology. The lighter traces on both time-series plots are the 30-year running averages, plotted on the middle (15th) year, of the projected annual streamflows, with the median trace shown as the dark dashed line. The 30-year average of the 1988–2017 'Stress Test" observed natural streamflow is shown as a black square. The box-whiskers plots show the distribution of the 30-year average values at 2055 (2041–2070); the outer boxes show the 10th and 90th percentiles; the inner boxes show the 25th, 50th, and 75th percentiles, and the max/min are shown at the ends of the whiskers. (Data: N. Mizukami, NCAR)

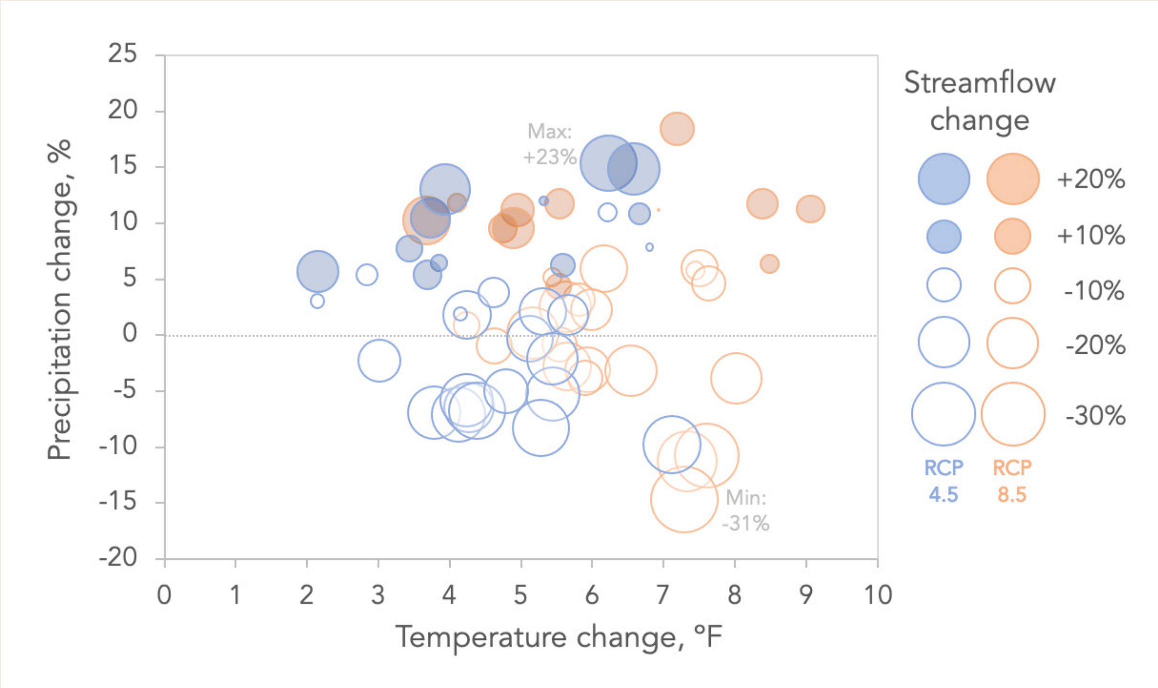

Figure 11.13

Projected future streamflow changes at Lees Ferry for 2041-2070 (2055) relative to the 1971-2000 baseline, and the projected temperature and precipitation changes associated with each projection of streamflow change. About two-thirds of the 64 projections show future decreases in streamflow, many of them despite increases in annual precipitation. These CMIP5-LOCA data are the same as those shown in Figures 11.10-11.12. (Streamflow projection data: N. Mizukami, NCAR; Temperature and precipitation projection data: D. Pierce, Scripps Institution; http://loca.ucsd.edu; Pierce, Cayan, and Thrasher 2014)

Figure 11.13 shows the same projected streamflow changes for the 2055-centered period as in the box-whiskers plots in Figure 11.12, but as a function of the projected annual temperature changes (as in Figure 11.10) and the projected annual precipitation changes (as in Figure 11.11). Each circle is an individual CMIP5-LOCA projection (32 under RCP 4.5; 32 under RCP 8.5); filled circles indicate a projected increase in streamflow, while open circles indicate a decrease in streamflow. The size of the circle indicates the magnitude of the change. The position of each circle in the scatterplot shows the projected temperature and precipitation changes associated with that same projection's streamflow change. Across both RCPs, about two-thirds of the projections (42 of 64) show decreasing streamflows, in many cases despite increasing annual precipitation. The largest decreases in streamflow (-20% or more) are associated with moderate or high increases in temperature (>4°F), and decreases in precipitation of 5-15%. Conversely, projected increases in streamflow are only associated with increases in precipitation of 5% or more.

SPOTLIGHT

GCM simulation of natural climate variability and implications for streamflow projections

As mentioned earlier in this chapter, GCMs simulate fundamental physical processes within and between thousands of grid cells arrayed across the face of the Earth and vertically up into the atmosphere and down into the oceans. Natural (or "internal") variability is not "programmed into" these models—it emerges as a consequence of the simulation of physical processes at very short time scales, accumulating into physically realistic behavior of the atmosphere and oceans at longer time scales, including the familiar modes of climate variability such as ENSO.

Each historical simulation or future projection from a GCM contains an expression of internal variability that is unique to that one simulation. GCM simulations over the historical period do not attempt to replicate the actual events and sequences of the observed climate, such as historical wet and dry years as observed in particular regions; however, the events and sequences that are simulated by the GCM over the historical period should be consistent with the statistical characteristics of the historical natural variability. GCM projections of future conditions can and often do show changes in variability relative to the historical period, such as greater interannual variability in precipitation over most regions (Pendergrass et al. 2017).

The simulated internal variability in any one GCM projection—whether over the historical period or a future period—will not be synchronized with the variability seen in projections from other GCMs. If the initial conditions of the atmosphere and ocean at the start of the simulation are varied, even minutely, then projections from the same GCM will develop different variability, due to the sensitivity of the modeled variability on the initial conditions.

As explained in Chapter 2, the observed variability in annual precipitation is much greater than the variability in temperature, relative to long-term observed trends in the two variables. The same is true in future projections: the projected internal variability in precipitation is much greater than that in temperature, relative to the expected anthropogenically forced trends.

This simulated internal variability strongly influences the projections of future hydrologic change in the Colorado River Basin and the way they are interpreted. Harding, Wood, and Prairie (2012) analyzed the large ensemble of 112 CMIP3-based hydrology projections and separately visualized multiple runs that came from a single GCM, which clearly highlights the large role of simulated multidecadal natural variability in the spread of projected streamflow changes for the Upper Basin.

Figure 11.14 shows 17 downscaled projections of Upper Basin annual temperature and precipitation from a single GCM, and 17 traces of VIC-modeled streamflows based on those climate projections. Note that for precipitation, the spread due to internal variability alone is relatively large, and this spread in precipitation is then carried forward into the streamflow traces. The forced trends in precipitation are hard to discern given the internal variability. Temperature, in contrast, has a much clearer forced trend: the traces follow the respective forcing of the emissions scenarios and the forced trend is much larger than the natural variability in temperature. That said, the spread of the temperature traces under each scenario at 2050 is not trivial (roughly 0.5°F–1.5°F).

Analyses of a larger ensemble of projections (n = 40) driven by a single emissions scenario from the same GCM (NCAR CCSM3), likewise found that regional changes and trends in temperature and precipitation around the globe are strongly influenced by GCM-simulated natural variability (Deser, Knutti, et al. 2012; Deser, Phillips, et al. 2012). That work and that of Harding, Wood, and Prairie (2012) also indicate that apparent disagreement between different GCMs regarding future regional change can stem from these unaligned and essentially random expressions of multidecadal variability, rather than from different predictions of the future forced change. For example, a "dry" projection of a region of interest from one GCM could be an outlier relative to an overall wet tendency of that GCM if one evaluated a larger set of projections for that region. These large ensembles can also help assess whether the internal variability simulated by the GCMs is similar to the observed variability (McKinnon et al. 2017).

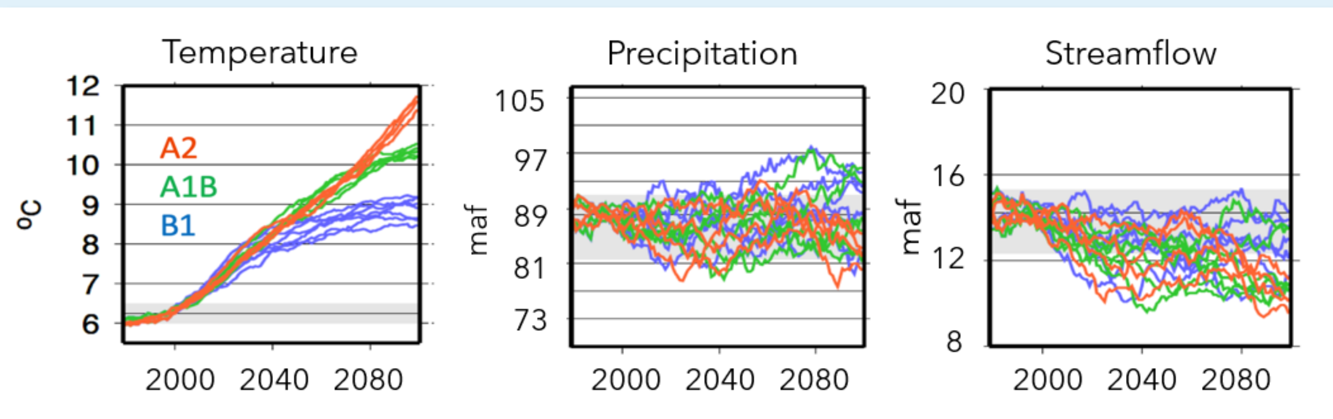

Figure 11.14

Single-GCM (NCAR CCM3) downscaled projections of (left) Upper Basin average annual temperature; (center) Upper Basin average annual precipitation; and (right) annual Colorado River streamflow at Lees Ferry, shown as running 30-year averages plotted on the last year. All 17 projections came from the same GCM, the NCAR CCM3 model, as generated for CMIP3. Projections are color-coded by emissions scenario. Within each emissions scenario (red, green, or blue), the differences among the traces are entirely due to the varying expressions of simulated internal (natural) variability over time. (Source: adapted from Harding, Wood, and Prairie 2012)

Results—future changes in annual Lower Basin runoff

Fewer studies have assessed potential future changes in Lower Basin runoff, that is, tributary flows to the Colorado mainstem. Also, the basin-wide assessments of future hydrology (e.g., Reclamation 2012e) have not reported on projected streamflows for the Lower Basin in the same level of detail as those for Lees Ferry. Studies that have assessed Lower Basin runoff changes, and other datasets that can be readily queried, generally show ranges of future hydrologic projections shifted strongly toward lower streamflows, as in the Upper Basin, but with drier overall outcomes (Table 11.5).

Table 11.5

Summary of results from studies since 2005 that have provided estimates of future changes in Lower Basin runoff. The studies are grouped according to primary GCM data and the methodology.

Methodology	Studies/assessments using these simulations	Results of these studies for Lower Basin runoff in mid-21st century	Comments
CMIP3 GCM projections + BCSD statistical downscaling + hydrologic model (VIC)	Reclamation (2012e)	Mean change for Virgin River, +3%; mean change for Bill Williams River, -4%	
CMIP3 GCM projections; runoff directly from the GCMs	Milly, Dunne, and Vecchia (2005)	Most (~87%) simulations show reduced runoff; median change -20% to -25%	
CMIP5 GCM projections + BCSD statistical downscaling + hydrologic model (VIC)	Reclamation (2020)	Median runoff change for grid boxes in Little Colorado and Salt-Verde headwaters: -10% to -25%	Runoff outcomes for Lower Basin not explicitly given; values here estimated from map of changes
CMIP5 GCM projections + other statistical downscaling + hydrologic model (simple water-balance model)	Alder and Hostetler (2015)	Most (~80%) simulations show reduced runoff; median change -15% (-25% to +10%)	Downscaled data used a variant of BCSD lacking the procedure that leads to 'wettening'

Results—future changes in other hydrologic variables and outcomes

Besides changes in annual runoff volumes, most studies based on datasets of hydrology projections for the basin as cited in Tables 11.4 and 11.5 have also reported future projections of other hydrologic variables, including snowpack, the timing of snowmelt and runoff, and soil moisture. Additional modeling studies have focused on one or more those variables. Below are summaries that generalize the findings of those datasets and studies. In general, the systematic changes to the hydrology of the basin that have been observed in recent decades, and at least partly driven by the warming trend (Chapter 2), are expected to continue, if not proceed more rapidly than in the past.

Snowpack

As with runoff, the various studies of hydrologic projections for the Upper Basin all show a strong tendency toward future basin-wide declines in April 1 SWE across the individual simulations (Christensen and Lettenmaier 2007; Reclamation 2011; 2012e, 2016b, 2020; Alder and Hostetler 2015), despite projected increases in winter and early spring precipitation in most GCM projections. Additional, snow-focused modeling studies that considered parts or all of the Upper Basin likewise strongly indicate future declines in spring snowpack (Battaglin, Hay, and Markstrom 2011; Lute, Abatzoglou, and Hegewisch 2015). Synthesizing across these studies, the general mid-range of the projected change in April 1 SWE by mid-century is roughly -10% to -20%. As with precipitation and runoff, the southern sub-basins are projected to more likely have declines in April 1 SWE, and larger declines than the northern sub-basins.

This strong tendency seen toward decreased April 1 SWE reflects multiple effects of the projected warming: a shift toward precipitation falling as rain instead of snow, greater sublimation and melt of the snowpack throughout the season, and a shift toward earlier snowmelt in the spring. These warming-related effects are strongly modulated by elevation, with snowpack at higher elevations seeing less impact from warming, as a percentage of current snowpack, than at lower elevations. Analysis of the CMIP5-BCSD hydrology projections also shows a tendency toward decreases in February 1 SWE and March 1 SWE in the Upper Basin, but not as strongly as for April 1 SWE (Lukas et al. 2014). May 1 and June 1 SWE, however, show sharp declines in nearly all of those projections, reflecting a broad shift toward earlier snowmelt.

The future persistence of the snowpack in the Lower Basin headwaters is at much greater risk than in the Upper Basin headwaters, facing larger projected declines in seasonal snowfall or peak SWE or both (Lute, Abatzoglou, and Hegewisch 2015; Christensen and Lettenmaier 2007). This is due to both the greater tendency toward projected declines in cool-season precipitation for the Lower Basin, and also because the current “snow climate” of the headwaters of the Lower Basin is substantially warmer and closer to the critical 0°C (32°F) threshold than in the Upper Basin (Lute, Abatzoglou, and Hegewisch 2015).

These snowpack projections also indicate that in the future, springtime SWE may become a less useful predictor of April–July streamflow and annual streamflow than it is currently (Livneh, Badger, and Lukas 2017).

Regardless of the future change in precipitation, the projected warming means that less of the annual precipitation in the headwaters would fall as snow, and that more of the snowpack would melt and run off prior to April 1, or other benchmark dates, than in the past.

Timing of snowmelt and runoff

The projections of future hydrology for the Upper Basin show much greater agreement regarding future change in the timing of snowmelt and peak runoff timing, and related changes in the annual hydrograph, than future change in annual runoff. Runoff timing is especially sensitive to warming, and nearly all projections, even ones with increased precipitation, show the peak of runoff shifting earlier, with the extent of that warming-driven shift ranging from 1–4 weeks by 2050, depending mainly on the GCM and emissions scenario.

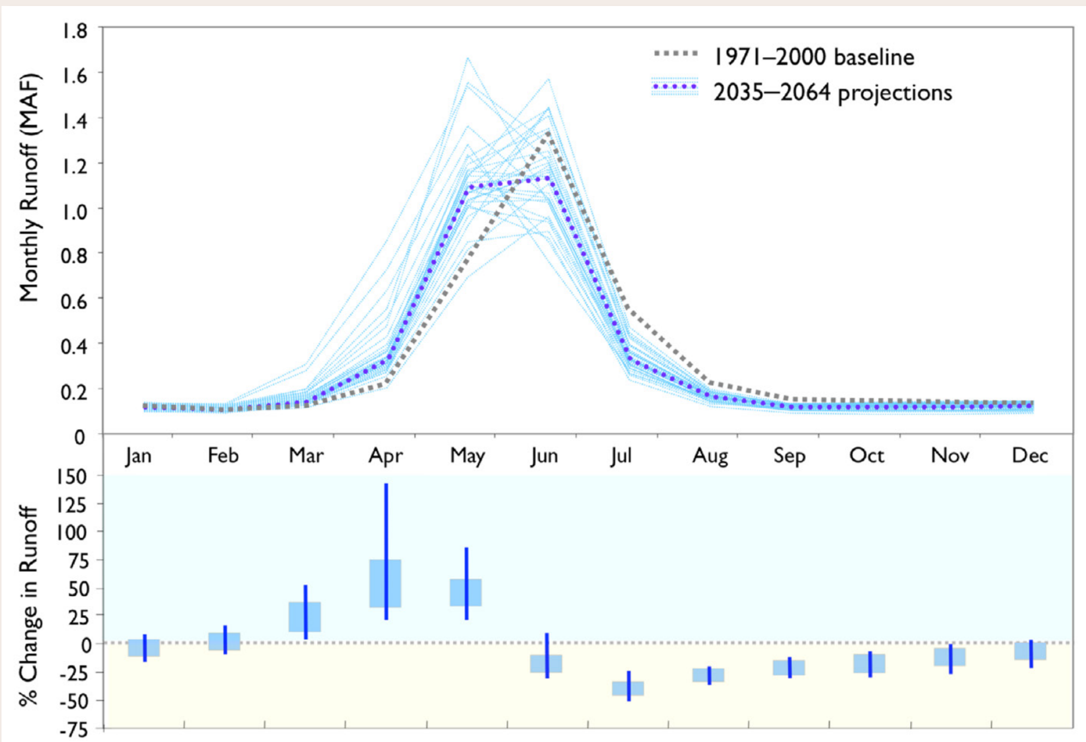

Figure 11.15

Projected monthly runoff change for the Colorado River headwaters for ~2050 (2035–2064) under RCP 4.5, from the CMIP5-BCSD dataset. Top: projected average monthly flows for the 31 projections (light blue lines) and the ensemble median (dark blue dotted line) compared to the 1971–2000 baseline (gray dashed line). Bottom: the corresponding ranges of the monthly runoff changes from that ensemble; the dark blue bars show the range from the 10th to 90th percentile and the light blue boxes show the 25th to 75th percentile. As the hydrograph shifts earlier, March–May runoff increases while June tends to decrease, and July–September runoff sharply decreases in all projections. (Source: Lukas et al. 2014; Data: http://gdo-dcp.ucllnl.org/downscaled_cmip_projections/)

Figure 11.15 is illustrative of the shift in the annual hydrograph seen in all of the GCM-based future hydrologies for the Upper Basin; here, CMIP5-BCSD projections of monthly runoff for the Colorado headwaters (i.e., at Glenwood Springs) for mid-century under RCP 4.5. That this shift is clearly seen in the CMIP5-BCSD hydrology, which has no overall tendency toward lower streamflow (Table 11.4), indicates how strongly earlier runoff timing is driven by warming temperatures. The shift toward earlier timing manifests as increases in monthly runoff in the spring months (March–May) in nearly all projections, while runoff decreases in summer and early fall (June–September) in nearly all projections, with the largest percentage decline in July. This general seasonal pattern of change is also seen in projections for the other sub-basins of the Upper Basin, as well as for snowmelt-dominated catchments in the Lower Basin.

As discussed in Chapter 2, some portion of the recent observed trend toward earlier runoff in the Upper Basin is due to the effect of dust-on-snow deposition—an effect that has not been explicitly included in the GCM-based studies, with the exception of Deems et al. (2013). If dust-on-snow deposition in the region continues to increase in the future, as it has recently (Clow, Williams, and Schuster 2016), the shift toward earlier runoff in the Upper Basin will occur faster than indicated by the GCM-based hydrology projections (Deems et al. 2013).

Changes in water demand

As stated in the Introduction, this report does not attempt a comprehensive treatment of estimates of water use and projections of future demand. But it is important to note here the projected effects of climate change on water demand, since they may be as significant as future changes in supply in tipping the water balance of the basin toward undesirable outcomes.

In a warmer climate, evaporative demand (i.e., potential evapotranspiration; PET) increases, which would increase the consumption of water by plants—whether in the context of agricultural crops, outdoor municipal vegetation, or phreatophytes—and would also increase evaporation from reservoirs. Estimating the magnitude of the future changes in water use first requires quantifying the PET change given changes in temperature, and then adjusting the temperature-driven changes in PET with changes in precipitation, if any.

The Colorado River Basin Water Supply and Demand Study (Reclamation 2012d) represented PET using the Penman-Monteith method (Chapter 5), both as that method is incorporated within the VIC model, and in separate adjustments for high-elevation areas. That analysis projected that for a 2060-centered period across an ensemble of CMIP3 projections, the agricultural demand adjustment factor would increase, on average, by 4-10% in 34 VIC grid cells representing important agricultural production areas in all seven basin states. An outdoor municipal demand factor for key urban areas in the basin increased by 4-10%, while reservoir evaporation increased by 3-5%. Nearly all of the changes in the demand factors were driven by temperature, with relatively small adjustments due to projected precipitation change. Basin-wide, the average projected total change in water demand for 2060, driven by climate alone, was an increase of 0.5 maf, with individual projections ranging from no change to an increase in water demand of over 1.0 maf.

The '"Exploring Climate and Hydrology Projections from the CMIP5 Archive" study (Reclamation 2020) repeated these analyses across large ensembles of both CMIP3 and CMIP5 projections, for a 2070-centered period. All demand factors were higher under CMIP5 than CMIP3, generally showing an increase of 6-15% for agricultural demand and outdoor municipal demand, over the 1971-2000 baseline. That study did not calculate a basin-wide change in total demand.

The Colorado River Water Availability Study (CRWAS; CWCB 2012), using CMIP3 projections of future temperature and precipitation, calculated changes in agricultural demand (Crop Irrigation Requirement; CIR) for a dozen areas in the Upper Basin in western Colorado. That analysis projected that the average annual CIR would increase by 18–37% for a 2070-centered period. The large discrepancy between the CRWAS results and those summarized above from Reclamation (2012d; 2020) can be attributed to the use of the Blaney-Criddle empirical PET method in the CRWAS analyses, which produces unrealistically large sensitivities of PET to increasing temperature for the higher-elevation sites in the basin (Reclamation 2012d; see also Chapter 5).

11.8 Interpreting climate change-informed hydrology in light of multiple uncertainties

Sources of uncertainty

Reviewing the history of studies of future basin hydrology in Table 11.4, it can be seen that the overall spread of potential future hydroclimatic changes in the Colorado River Basin has not been reduced by the development of new methods and the refinement of climate models—which is also true for global-scale projections of climate and hydrology. In fact, in the last several years, additional sources of uncertainty and error have been identified and more fully appreciated, if not quantified (Clark et al. 2016).

Table 11.6 summarizes the general sources of uncertainty in climate change-informed projections of future hydrology. Until recently, the construction of the various ensembles of downscaled CMIP3 and CMIP5 projections used in Colorado River Basin planning only reflected the first three sources of uncertainty: emissions scenarios, GCM model structure, and internal (i.e., natural) variability. The magnitude of natural climate variability simulated by the models and its effects on estimates of future change is larger than was understood in the late 2000s (Deser, Phillips, et al. 2012; Harding, Wood, and Prairie 2012), which complicates efforts to identify and tease apart the uncertainties from other sources. The remaining sources of uncertainty in Table 11.6 have not been adequately characterized: the choice of downscaling method and bias-correction method, the choice of observed climate dataset used for bias-correction, and the choice of hydrology model, all of which are key steps in the conventional top-down approach.

The quantifiable contributions of the first three sources to the uncertainty in projections of temperature, precipitation, and runoff for the Upper Basin, from the CMIP5-BCSD ensemble, are depicted in Figure 11.16. In the bottom row, of the total uncertainty in the 30-year average Upper Basin runoff in about 2050, the largest source is the differences among the GCMs ("model") in simulating the forced change in temperature and precipitation given the same emissions scenario. The second largest source is internal variability manifesting at the 30-year timescale, as also shown in the right-hand panel of Figure 11.14. The smallest source of uncertainty in runoff at 2050 is the choice of emissions scenario.

Interpreting the range of future potential outcomes

The potential future climate and hydrology outcomes for the Colorado River Basin depicted by the large CMIP-based ensembles have created frustration for planners and practitioners, mainly for two related factors. First, the range of projected future outcomes is very broad, with some future hydrologic traces showing significant increases in streamflow, and others showing significant decreases in streamflow. But this range needs to be kept in perspective: even if climate change were not occurring, water managers in the basin would still face large uncertainties about the trajectory of basin hydrology over the next several decades due to natural (internal) variability of the climate system alone, as indicated by the historical hydrology (Chapter 9), paleohydrology (Chapter 10), and ensembles of projections from a single climate model that highlight the magnitude of internal variability (Figure 11.14). Second, the sheer number of traces—often 100 or more—makes data handling, analysis, and interpretation unwieldy.

Table 11.6

Summary of sources of uncertainty in future hydrologic projection based on CMIP GCM runs. The sources in the first three rows are reasonably quantified; see Figure 11.15. T and P refer to temperature and precipitation, respectively.

Source of uncertainty	How this uncertainty can be discerned if not fully characterized	Is this feasible within a typical dataset of CMIP-based hydrologic projections?	Contribution to total uncertainty in projected Upper Basin climate changes	Contribution to total uncertainty in projected Upper Basin runoff changes
Emissions scenario	Look at the differences in the GCM ensemble under different RCPs	Partially— simulated natural variability can confound unless large ensembles from multiple models are available	T: Large P: Small	Small; increases to moderate by 2100
GCM structure and parameters, i.e., representation of key climate processes	Look at results from different GCMs under same RCP	Partially— simulated natural variability can confound unless large ensembles from multiple models are available	T: Large, but decreases by 2100 P: Large	Large
Decadal and multi-decadal natural (internal) variability	Look across multiple runs from a single GCM under the same RCP	Partially— most CMIP GCMs have only 1 run per RCP, but some have multiple runs	T: Small P: Moderate; confounds interpretation of T and P changes	Moderate; decreases toward late 21st century
Downscaling method (including bias-correction)	Compare results from at least two methods	No— most existing datasets use one or a few very similar methods	*Unclear; locally can be large, especially for precipitation*	*Unclear; locally can be large*
Gridded climate data used for statistical downscaling and calibrating RCMs	Compare results using different gridded climate datasets, with all else equal	No— existing datasets use one gridded observational dataset	*Unclear*	*Unclear*
Hydrologic model structure and parameters	Compare results using different hydrologic models, with all else equal	No— most datasets use one hydrologic model with one set of parameters	N/A	*Unclear; locally can be large*

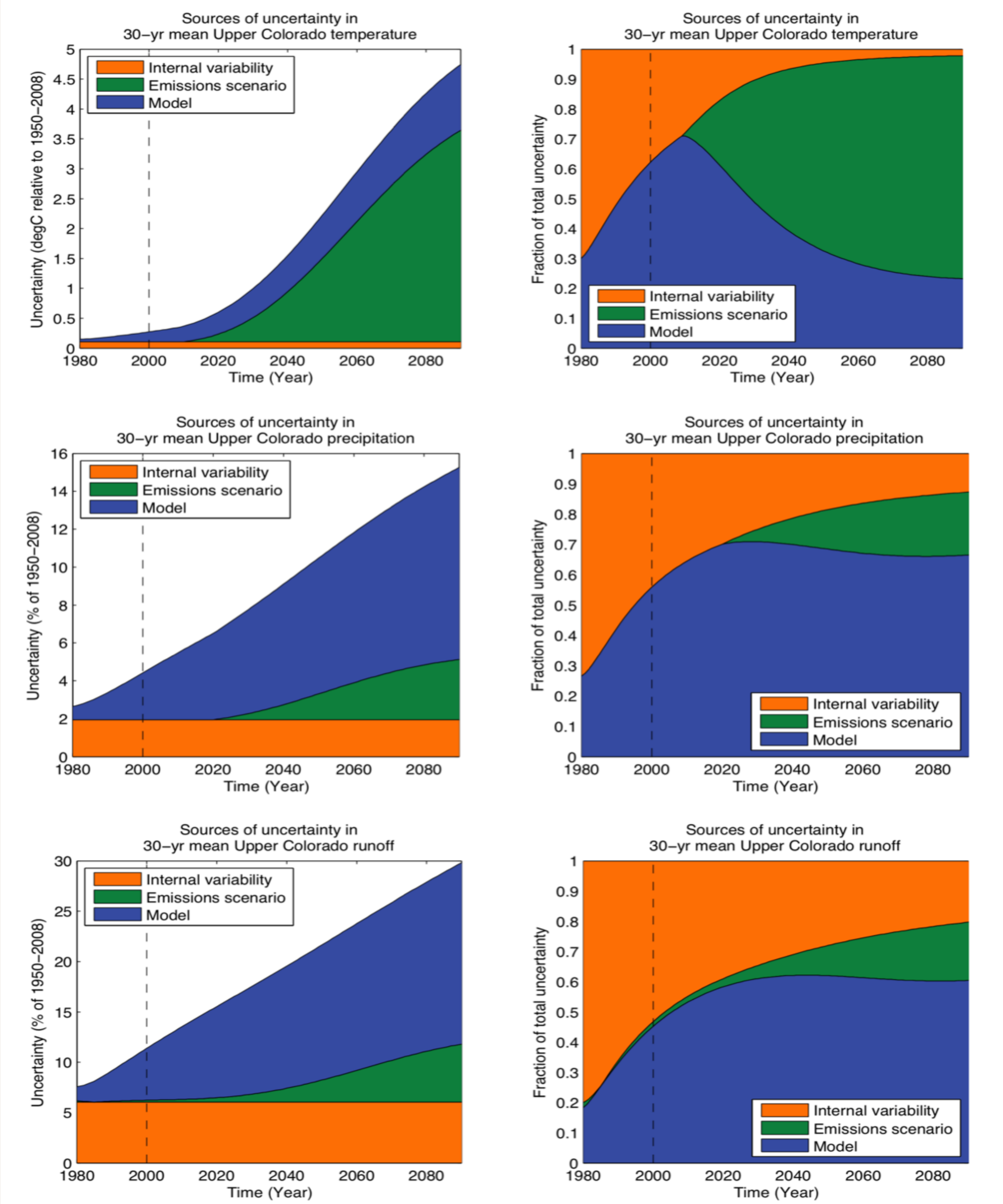

Figure 11.16

Quantification of three key sources of uncertainty (i.e., ensemble spread) in CMIP5 BCSD projections of Upper Basin temperature (upper), precipitation (middle), and runoff (lower): Internal (or natural) variability; Emissions scenario, and Model (GCM) structure and parameters. The left-right pairs of plots show the same data in different ways: (left) the uncertainty associated with each source relative to the observed mean of that variable, and (right) as a fraction of the total uncertainty at that time period. (Source: F. Lehner, NCAR, based on plots by Hawkins and Sutton 2009; Data: http://gdo-dcp.ucllnl.org/)

In response to both of these factors, it can be tempting for users to interpret a CMIP-based ensemble of hydroclimate projections in probabilistic terms, e.g., assuming that the mid-point of the ensemble range is more likely than the projections nearer the ends of the range, and focusing on that number. Some judgment of the likelihood of future outcomes is needed in order to allocate resources in most planning paradigms (Schneider 2002). But as noted earlier, the ensembles of GCM projections may be biased by similarity between GCMs stemming from shared development environments and model code. Furthermore, it is believed that even a large ensemble will under-sample the multi-variate space potentially occupied by the future climate; the actual climate may end up outside of the range of the CMIP projections (Stainforth et al. 2007; Shepherd et al. 2018). Accordingly, it should not be automatically *assumed* that the mean or median of the ensemble is the most likely outcome—or that the 90th percentile of the ensemble actually has a 10% likelihood of being exceeded, and so on. Climate researchers have attempted to correct the distributions of regional projected climate change to account for this cross-GCM similarity, though the corrected distributions were even broader, with heavier tails, and the centers of the distributions were often shifted (Steinschneider et al. 2015). Thus, taking the distribution of projected changes (e.g., the box-whiskers plots in Figures 11.10-11.12) at face value as a quantitative measure of future risk is not advisable.

However, this does not mean the distribution of the CMIP ensembles tell us nothing. There is very strong confidence in future warming in general, and that higher emissions scenarios lead to greater warming. The overall shifts in hydroclimate seen in the CMIP-based ensembles—toward lower spring snowpacks, earlier melt and runoff, lower annual runoff volumes, and increasing water demand—are driven largely or almost entirely by the warming. In other words, there are compelling physical mechanisms behind the most relevant hydrologic changes depicted in the ensembles. It is reasonable, then, to take the ensembles as a starting point for exploration of the system consequences.

One way to do this, while also reducing the number of individual traces to deal with when evaluating impacts, is a scenario approach in which several discrete hydroclimate scenarios are created, each based on a carefully selected subset of GCM projections, which cover most of the range or uncertainty across the projections. With only four or five future hydroclimate scenarios, more attention can be given to each pathway. Clark et al. (2016) laid out what they call a “hydrologic storylines” approach in which each storyline is a scenario derived from the traditional top-down methodology, with the collection of storylines representing a sampling of the range of future projections. Reclamation (in an Oklahoma case) and AMEC (CRWAS-II for Colorado; Harding 2015) have also proposed empirical approaches that create a small number of scenarios representing the spread of the ensemble. A storyline approach, with four future climate scenarios, was also adopted for the 4th California State Climate Assessment (Pierce, Kalansky, and Cayan 2018). An alternative storyline approach proposed by Shepherd et al. (2018) calls for evaluating the changes shown by the different combinations of GCMs, downscaling methods, and hydrology models according to the physical plausibility of the underlying causal mechanisms of these changes. The emphasis is on identifying those modeled future trajectories and changes, such as a northward shift in the typical storm track over the basin, that are linked to the most compelling physics-based and observationally validated explanations. In some cases, this may suggest physically plausible conditions beyond the ensemble range.

Other water system analysts have preferred approaches that keep the CMIP ensemble intact, in all of its diversity and breadth, but begin with the known system vulnerabilities. These bottom-up sensitivity analyses may, for example, create multi-dimensional climate response functions specific to a system outcome, and then plot how the ensemble of climate or hydrologic changes falls across that response surface or response space (e.g., Brown and Wilby 2012).

For now and the foreseeable future, the most reasonable conclusion is that there is no one best approach for addressing uncertainty in projections of future climate. The range and distribution of conditions across the ensemble are biased to an unknown degree, so likelihood should not be directly taken from the distribution—but the ensemble nevertheless contains useful information that should not be ignored.

For further reading and additional guidance on interpreting and applying climate change information in the context of water system planning, Vano et al. (2018) provide a concise and practical primer that also includes a table of additional reading with embedded links.

11.9 Challenges and opportunities

About a decade ago, multiple assessments conducted by, or on behalf of, Reclamation and other water agencies identified research needs and knowledge gaps related to climate change information used in water planning in the Colorado River Basin and the U.S. (Reclamation 2007a; Barsugli et al. 2009; Brekke et al. 2011). Reviewing the findings of these assessments, one is struck by how many of the needs and gaps have persisted over the intervening decade, despite the cumulative investment by the research and practitioner communities.

This is not to say that scientific understanding and technical capacity have not progressed. In particular, there is now much improved availability of regional climate projection datasets from statistically and dynamically downscaled methods (Table 11.3), and many of these datasets provide daily data that are suitable for analyzing changes in climate extremes. There is also much greater understanding and appreciation, and even quantification, of the different sources of uncertainty in climate change-informed hydrology for the basin. This has included evaluations of different datasets and models (though often not comprehensive enough) for the different steps of the top-down chain.

The list below summarizes several remaining challenges in the development and usability of climate change-informed hydrology, and the opportunities for further improvement in this area. Note that few of these are directed at the research community alone, which indicates that in many cases, the path to greater actionability is not necessarily found in the refinement of models, quantitative methods, or datasets.

Challenge

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

Opportunities

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

Challenge

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

Opportunities

- Methods are available (e.g., scenario development, hydrologic storylines) to at least reduce the number of traces from the ensemble, improving their tractability for planning, and potentially identifying more physically plausible and likely outcomes.

- Alternative planning paradigms may be more appropriate for decision making under deep uncertainty. In planning, emphasize those outcomes associated with greater vulnerability and impacts, i.e., drier projections.

Challenge

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

Opportunity

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

Challenge

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

Opportunity

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

Challenge

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

Opportunities

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

Challenge

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

Opportunities

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

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Glossary

ablation
The loss of snow from the snowpack due to melting, evaporation, or wind.

absolute error
The difference between the measured and actual values of *x*.

albedo
The percentage of incoming light that is reflected off of a surface.

aleatory uncertainty
Uncertainty due to randomness in the behavior of a system (i.e., natural variability)

anomaly
A deviation from the expected or normal value.

atmospheric river (AR)
A long and concentrated plume of low-level (<5,000’) moisture originating in the tropical Pacific.

autocorrelation
Correlation between consecutive values of the same time series, typically due to time-dependencies in the dataset.

bank storage
Water that seeps into and out of the bed and banks of a stream, lake, or reservoir depending on relative water levels.

bias correction
Adjustments to raw model output (e.g., from a climate model, or streamflow forecast model) using observations in a reference period.

boundary conditions
Conditions that govern the evolution of climate for a given area (e.g., ocean heat flux, soil moisture, sea-ice and snowpack conditions) and can help forecast the future climate state when included in a model.

calibration
The process of comparing a model with the real system, followed by multiple revisions and comparisons so that the model outputs more closely resemble outcomes in the real system.

climate forcing
A factor causing a difference between the incoming and outgoing energy of the Earth’s climate system, e.g., increases in greenhouse-gas concentrations.

climatology
In forecasting and modeling, refers to the historical average climate used as a baseline (e.g., “compared to climatology”). Synonymous with climate normal.

coefficient of variation (CV)
A common measure of variability in a dataset; the standard deviation divided by the mean.

consumptive use
The amount of diverted water that is lost during usage via evapotranspiration, evaporation, or seepage and is thus unavailable for subsequent use.

convection
The vertical transport of heat and moisture in the atmosphere, typically due to an air parcel rising if it is warmer than the surrounding atmosphere.

covariate
A variable (e.g., temperature) whose value changes when the variable under study changes (e.g., precipitation).

cross-correlation
A method for estimating to what degree two variables or datasets are correlated.

cumulative distribution function (CDF)
A function describing the probability that a random variable, such as streamflow, is less than or equal to a specified value. CDF-based probabilities are often expressed in terms of percent exceedance or non-exceedance.

Darcy's Law
The mathematical expression that describes fluid flow through a porous medium (e.g., soil).

datum
The base, or 0.0-foot gage-height (stage), for a stream gage.

dead pool
The point at which the water level of a lake or reservoir is so low, water can no longer be discharged or released downstream.

deterministic
Referring to a system or model in which a given input always produces the same output; the input strictly determines the output.

dewpoint
The local temperature that the air would need to be cooled to (assuming atmospheric pressure and moisture content are constant) in order to achieve a relative humidity (RH) of 100%.

dipole
A pair of two equal and opposing centers of action, usually separated by a distance.

discharge
Volume of water flowing past a given point in the stream in a given period of time; synonymous with streamflow.

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

downscaling
Method to take data at coarse scales, e.g., from a GCM, and translate those data to more local scales.

dynamical
In modeling, refers to the use of a physical model, i.e., basic physical equations represent some or most of the relevant processes.

environmental flow
Water that is left in or released into a river to manage the quantity, quality, and timing of flow in order to sustain the river's ecosystem.

epistemic uncertainty
Uncertainty due to incomplete knowledge of the behavior of a system.

evapotranspiration
A combination of evaporation from the land surface and water bodies, and transpiration of water from plant surfaces to the atmosphere. Generally includes sublimation from the snow surface as well.

fixed lapse rate
A constant rate of change of an atmospheric variable, usually temperature, with elevation.

flow routing
The process of determining the flow hydrograph at sequential points along a stream based on a known hydrograph upstream.

forcing - see **climate forcing or weather forcing**

forecast
A prediction of future hydrologic or climate conditions based on the initial (current) conditions and factors known to influence the evolution of the physical system.

Gaussian filter
A mathematical filter used to remove noise and emphasize a specific frequency of a signal; uses a bell-shaped statistical distribution.

gridded data
Data that is represented in a two-dimensional gridded matrix of graphical contours, interpolated or otherwise derived from a set of point observations.

heat flux
The rate of heat energy transfer from one surface or layer of the atmosphere to the next.

hindcast
A forecast run for a past date or period, using the same model version as for real-time forecasts; used for model calibration and to "spin up" forecast models. Same as **reforecast**.

hydraulic conductivity
A measure of the ease with which water flows through a medium, such as soil or sediment.

hydroclimate
The aggregate of climatic and hydrologic processes and characteristics, and linkages between them, for a watershed or region.

hydrograph
A graph of the volume of water flowing past a location per unit time.

hydrometeorology
A branch of meteorology and hydrology that studies the transfer of water and energy between the land surface and the lower atmosphere.

imaging spectrometer
An instrument used for measuring wavelengths of light spectra in order to create a spectrally-resolved image of an object or area.

in situ
Referring to a ground-based measurement site that is fixed in place.

inhomogeneity
A change in the mean or variance of a time-series of data (such as weather observations) that is caused by changes in the observing station or network, not in the climate itself.

Interim Guidelines
The Colorado River Interim Guidelines for Lower Basin Shortages and Coordinated Operations for Lake Powell and Lake Mead, signed by the Secretary of the Interior in December 2007. The guidelines expire in 2026. https://www.usbr.gov/lc/region/programs/strategies.html

internal variability
Variability in climate that comes from chaotic and unpredictable fluctuations of the Earth's oceans and atmosphere.

interpolation
The process of calculating the value of a function or set of data between two known values.

isothermal
A dynamic in which temperature remains constant while other aspects of the system change.

jet stream
A narrow band of very strong winds in the upper atmosphere that follows the boundary between warmer and colder air masses.

kriging
A smoothing technique that calculates minimum error-variance estimates for unsampled values.

kurtosis
A measure of the sharpness of the peak of a probability distribution.

lag-1 autocorrelation
Serial correlation between data values at adjacent time steps.

lapse rate
The rate of change of an atmospheric variable, such as temperature, with elevation. A lapse rate is adiabatic when no heat exchange occurs between the given air parcel and its surroundings.

latency
The lag, relative to real-time, for producing and releasing a dataset that represents real-time conditions.

latent heat flux
The flow of heat from the Earth's surface to the atmosphere that involves evaporation and condensation of water; the energy absorbed/released during a phase change of a substance.

Law of the River
A collection of compacts, federal laws, court decisions and decrees, contracts, and regulatory guidelines that apportions the water and regulates the use and management of the Colorado River among the seven basin states and Mexico.

LiDAR (or lidar)
Light detection and ranging; a remote sensing method which uses pulsed lasers of light to measure the variable distances from the sensor to the land surface.

longwave radiation
Infrared energy emitted by the Earth and its atmosphere at wavelengths between about 5 and 25 micrometers.

Lower Basin
The portions of the Colorado River Basin in Arizona, California, Nevada, New Mexico and Utah that are downstream of the Colorado River Compact point at Lee Ferry, Arizona.

lumped model
In hydrologic modeling, a lumped model represents individual sub-basins or elevation zones as a single unit, averaging spatial characteristics across that unit. Contrast with **distributed model.**

Markov chain
A mathematical system in which transitions from one state to another are dependent on the current state and time elapsed.

megadrought
A sustained and widespread drought that lasts at least 10-15 years, though definitions in the literature have varied.

metadata
Data that gives information about other data or describes its own dataset.

mid-latitude cyclone
A large (~500-2000 km) storm system that has a low-pressure center, cyclonic (counter-clockwise) flow, and a cold front. Over the western U.S., mid-latitude cyclones almost always move from west to east and are effective at producing precipitation over broad areas.

Minute 319
The binding agreement signed in 2012 by the International Boundary and Water Commission, United States and Mexico, to advance the 1944 Water Treaty between both countries and establish better basin operations and water allocation, and humanitarian measures.

Modoki
An El Niño event that has its warmest SST anomalies located in the central equatorial Pacific; same as "CP" El Niño.

multicollinearity
A condition in which multiple explanatory variables that predict variation in a response variable are themselves correlated with each other.

multiple linear regression
A form of regression in which a model is created by fitting a linear equation over the observed data, typically for two or more explanatory (independent) variables and a response (dependent) variable.

multivariate
Referring to statistical methods in which there are multiple response (dependent) variables being examined.

natural flow
Gaged flow that has been adjusted to remove the effects of upstream human activity such as storage or diversion. Equivalent to **naturalized flow**, **virgin flow**, and **undepleted flow**.

naturalized flow – see *natural flow*

nearest neighbor method
A nonparametric method that examines the distances between a data point (e.g., a sampled value) and the closest data points to it in *x-y* space ("nearest neighbors," e.g., historical values) and thereby obtains either a classification for the data point (such as wet, dry, or normal) or a set of nearest neighbors (i.e., K-NN).

nonparametric
A statistical method that assumes no underlying mathematical function for a sample of observations.

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

p
A statistical hypothesis test; the probability of obtaining a particular result purely by chance; a test of statistical significance.

paleohydrology
The study of hydrologic events and processes prior to the instrumental (gaged) record, typically using environmental proxies such as tree rings.

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

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

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

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

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

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

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

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

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

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

r
Correlation coefficient. The strength and direction of a linear relationship between two variables.

R^2
Coefficient of determination. The proportion of variance in a dependent variable that's explained by the independent variables in a regression model.

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

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

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

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

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

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

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

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

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

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

return flow
The water diverted from a river or stream that returns to a water source and is available for consumptive use by others downstream.

runoff
Precipitation that flows toward streams on the surface of the ground or within the ground. Runoff as it is routed and measured within channels is *streamflow*.

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

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

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

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

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

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

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

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

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

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

statistically significant
Unlikely to occur by chance alone, as indicated by one of several statistical tests.

stepwise regression
The process of building a regression model from a set of values by entering and removing predictor variables in a step-by-step manner.

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

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

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

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

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

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

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

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

tilt
A shift in probabilities toward a certain outcome.

transpiration
Water discharged into the atmosphere from plant surfaces.

troposphere
The layer of the atmosphere from the Earth's surface up to the tropopause (~11–15 km) below the stratosphere; characterized by decreasing temperature with height, vertical wind motion, water vapor content, and sensible weather (clouds, rain, etc.).

undercatch
When less precipitation is captured by a precipitation gage than actually falls; more likely to occur with snow, especially under windy conditions.

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

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

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

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

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

Acronyms & Abbreviations

24MS
24-Month Study Model

AET
actual evapotranspiration

AgriMET
Cooperative Agricultural Weather Network

AgWxNet
Agricultural Weather Network

AHPS
Advanced Hydrologic Prediction Service

ALEXI
Atmosphere-Land Exchange Inversion

AMJ
April-May-June

AMO
Atlantic Multidecadal Oscillation

ANN
artificial neural network

AOP
Annual Operating Plan

AR
atmospheric river

AR-1
first-order autoregression

ARkStorm
Atmospheric River 1,000-year Storm

ASCE
American Society of Civil Engineers

ASO
Airborne Snow Observatory

ASOS
Automated Surface Observing System

AVHRR
Advanced Very High-Resolution Radiometer

AWOS
Automated Weather Observing System

BCCA
Bias-Corrected Constructed Analog

BCSD
Bias-Corrected Spatial Disaggregation (downscaling method)

BCSD5
BCSD applied to CMIP5

BOR
United States Bureau of Reclamation

BREB
Bowen Ratio Energy Balance method

C3S
Copernicus Climate Change Service

CA
Constructed Analogues

CADSWES
Center for Advanced Decision Support for Water and Environmental Systems

CADWR
California Department of Water Resources

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

CBRFC
Colorado Basin River Forecast Center

CCA
Canonical Correlation Analysis

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

CDEC
California Data Exchange Center

CDF
cumulative distribution function

CESM
Community Earth System Model (global climate model)

CFS
Climate/Coupled Forecast System

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

CHPS
Community Hydrologic Prediction System

CIMIS
California Irrigation Management Information System

CIR
crop irrigation requirement

CIRES
Cooperative Institute for Research in Environmental Sciences

CLIMAS
Climate Assessment for the Southwest

CLM
Community Land Model

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

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

CNRFC
California-Nevada River Forecast Center

CoAgMET
Colorado Agricultural Meteorological Network

CoCoRaHS
Community Collaborative Rain, Hail and Snow Network

CODOS
Colorado Dust-on-Snow

CONUS
contiguous United States (the lower 48 states)

COOP
Cooperative Observer Program

CP
Central Pacific

CPC
Climate Prediction Center

CRB
Colorado River Basin

CRBPP
Colorado River Basin Pilot Project

CRPSS
Continuous Ranked Probability Skill Score

CRSM
Colorado River Simulation Model

CRSP
Colorado River Storage Project

CRSS
Colorado River Simulation System

CRWAS
Colorado River Water Availability Study
CSAS

CRWAS
Center for Snow and Avalanche Studies

CTSM
Community Terrestrial Systems Model

CU
consumptive use

CUL
consumptive uses and losses

CV
coefficient of variation

CVP/SWP
Central Valley Project/State Water Project

CWCB
Colorado Water Conservation Board

CWEST
Center for Water, Earth Science and Technology

DA
data assimilation

Daymet v.3
daily gridded surface meteorological data

DCP
Drought Contingency Plan

DEM
digital elevation model

DEOS
Delaware Environmental Observing System

DHSVM
Distributed Hydrology Soil Vegetation Model

DJF
December-January-February

DMDU
Decision Making Under Deep Uncertainty

DMI
Data Management Interface

DOD
Department of Defense

DOE
Department of Energy

DOW
Doppler [radar] on Wheels

DRI
Desert Research Institute

DTR
diurnal temperature range

EC
eddy-covariance method

EC
Environment Canada

ECCA
ensemble canonical correlation analysis

ECMWF
European Centre for Medium-Range Weather Forecasts

EDDI
Evaporative Demand Drought Index

EFAS
European Flood Awareness System

EIS
Environmental Impact Statement

En-GARD
Ensemble Generalized Analog Regression Downscaling

ENSO
El Niño-Southern Oscillation

EOF
empirical orthogonal function

EP
Eastern Pacific

ERC
energy release component

ESI
Evaporative Stress Index

ESM
coupled Earth system model

ESP
ensemble streamflow prediction

ESRL
Earth System Research Laboratory

ET
evapotranspiration

ET_0
Reference (crop) evapotranspiration

EVI
Enhanced Vegetation Index

FAA
Federal Aviation Administration

FAWN
Florida Automated Weather Network

FEWS
Famine Early Warning System

FEWS
Flood Early Warning System

FIRO
forecast-informed reservoir operations

FLOR
Forecast-oriented Low Ocean Resolution (global climate model)

FORTRAN
Formula Translation programming language

FPS
Federal Priority Streamgages

FROMUS
Forecast and Reservoir Operation Modeling Uncertainty Scoping

fSCA
fractional snow covered area

FWS
U.S. Fish and Wildlife Service

GCM
global climate model, or general circulation model

GEFS
Global Ensemble Forecast System

GEM
Global Environmental Multiscale model

GEOS
Goddard Earth Observing System (global climate model)

GeoTiff
Georeferenced Tagged Image File Format

GFDL
Geophysical Fluid Dynamics Laboratory

GFS
Global Forecast System model

GHCN
Global Historical Climatology Network

GHCN-D
Global Historical Climate Network-Daily

GHG
greenhouse gas

GIS
geographic information system

GLOFAS
Global Flood Awareness System

GLOFFIS
Global Flood Forecast Information System

GOES
Geostationary Operational Environmental Satellite

GRACE
Gravity Recovery and Climate Experiment

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

gridMET
Gridded Surface Meteorological dataset

GSSHA
Gridded Surface/Subsurface Hydrologic Analysis

GW
groundwater

HCCD
Historical Canadian Climate Data

HCN
Historical Climatology Network

HDA
hydrologic data assimilation

HDSC
Hydrometeorological Design Studies Center

HEFS
Hydrologic Ensemble Forecast Service

HESP
Hierarchical Ensemble Streamflow Prediction

HL-RDHM
Hydrologic Laboratory-Research Distributed Hydrologic Model

HMT
Hydromet Testbed

HP
hydrological processor

HRRR
High Resolution Rapid Refresh (weather model)

HSS
Heidke Skill Score

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

HUC
Hydrologic Unit Code

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

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

ICAR
Intermediate Complexity Atmospheric Research model

ICS
intentionally created surplus

IDW
inverse distance weighting

IFS
integrated forecast system

IHC
initial hydrologic conditions

INSTAAR
Institute of Arctic and Alpine Research

IPCC
Intergovernmental Panel on Climate Change

IPO
Interdecadal Pacific Oscillation

IRI
International Research Institute

iRON
Interactive Roaring Fork Observing Network

ISM
Index Sequential Method

JFM
January-February-March

JJA
June-July-August

K-NN
K-Nearest Neighbor

Landsat
Land Remote-Sensing Satellite (System)

LAST
Lane's Applied Stochastic Techniques

LERI
Landscape Evaporative Response Index

lidar
light detection and ranging

LOCA
Localized Constructed Analog

LSM
land surface model

M&I
municipal and industrial (water use category)

MACA
Multivariate Adaptive Constructed Analog

maf
million acre-feet

MAM
March-April-May

MEFP
Meteorological Ensemble Forecast Processor

METRIC
Mapping Evapotranspiration at high Resolution with Internalized Calibration

MJO
Madden-Julian Oscillation

MMEFS
Met-Model Ensemble Forecast System

MOCOM
Multi-Objective Complex evolution

MODDRFS
MODIS Dust Radiative Forcing in Snow

MODIS
Moderate Resolution Imaging Spectroradiometer

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

MODSCAG
MODIS Snow Covered Area and Grain-size

MPR
Multiscale Parameter Regionalization

MRM
Multiple Run Management

MT-CLIM (or MTCLIM)
Mountain Climate simulator

MTOM
Mid-Term Probabilistic Operations Model

NA-CORDEX
North American Coordinated Regional Downscaling Experiment

NAM
North American Monsoon

NAO
North Atlantic Oscillation

NARCCAP
North American Regional Climate Change Assessment Program

NARR
North American Regional Reanalysis

NASA
National Aeronautics and Space Administration

NASA JPL
NASA Jet Propulsion Laboratory

NCAR
National Center for Atmospheric Research

NCCASC
North Central Climate Adaptation Science Center

NCECONET
North Carolina Environment and Climate Observing Network

NCEI
National Centers for Environmental Information

NCEP
National Centers for Environmental Prediction

nClimDiv
new Climate Divisional (NOAA climate dataset)

NDBC
National Data Buoy Center

NDVI
Normalized Difference Vegetation Index

NDWI
Normalized Difference Water Index

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

NevCan
Nevada Climate-ecohydrological Assessment Network

NGWOS
Next-Generation Water Observing System

NHMM
Bayesian Nonhomogenous Hidden Markov Model

NICENET
Nevada Integrated Climate and Evapotranspiration Network

NIDIS
National Integrated Drought Information System

NLDAS
North American Land Data Assimilation System

NMME
North American Multi-Model Ensemble

NN R1
NCEP/NCAR Reanalysis

NOAA
National Oceanic and Atmospheric Administration

NOAH
Neural Optimization Applied Hydrology

Noah-MP
Noah-Multi-parameterization Model

NOHRSC
National Operational Hydrologic Remote Sensing Center

NPP
Nonparametric paleohydrologic method

NRCS
Natural Resource Conservation Service

NSF
National Science Foundation

NSIDC
National Snow and Ice Data Center

NSMN
National Soil Moisture Network

NVDWR
Nevada Department of Water Resources

NWCC
National Water and Climate Center

NWIS
National Water Information System

NWM
National Water Model

NWP
numerical weather prediction

NWS
National Weather Service

NWSRFS
National Weather Service River Forecast System

NZI
New Zealand Index

OCN
Optimal Climate Normals

OHD
Office of Hydrologic Development

OK Mesonet
Oklahoma Mesoscale Network

ONI
Oceanic Niño Index

OWAQ
Office of Weather and Air Quality

OWP
Office of Water Prediction

PC
principal components

PCA
principal components analysis

PCR
principal components regression

PDO
Pacific Decadal Oscillation

PDSI
Palmer Drought Severity Index

PET
potential evapotranspiration

PGW
pseudo-global warming

PRISM
Parameter-elevation Relationships on Independent Slopes Model

PSD
Physical Sciences Division

QBO
Quasi-Biennial Oscillation

QDO
Quasi-Decadal Oscillation

QM
quantile mapping

QPE
Quantitative Precipitation Estimate

QPF
Quantitative Precipitation Forecast

QTE
Quantitative Temperature Estimate

QTF
Quantitative Temperature Forecast

radar
radio detection and ranging

RAP
Rapid Refresh (weather model)

RAWS
Remote Automated Weather Station Network

RCM
Regional Climate Model

RCP
Representative Concentration Pathway

RE
reduction-of-error

RFC
River Forecast Center

RFS
River Forecasting System

RH
relative humidity

RiverSMART
RiverWare Study Manager and Research Tool

RMSE
root mean squared error

S/I
seasonal to interannual

S2S
subseasonal to seasonal

Sac-SMA
Sacramento Soil Moisture Accounting Model

SAMS
Stochastic Analysis Modeling and Simulation

SCA
snow-covered area

SCAN
Soil Climate Analysis Network

SCE
Shuffled Complex Evolution

SCF
seasonal climate forecast

SE
standard error

SECURE
Science and Engineering to Comprehensively Understand and Responsibly Enhance Water

SFWMD
South Florida Water Management District

SM
soil moisture

SMA
Soil Moisture Accounting

SMAP
Soil Moisture Active Passive

SMHI
Swedish Meteorological and Hydrological Institute

SMLR
Screening Multiple Linear Regression

SMOS
Soil Moisture and Ocean Salinity

SNODAS
Snow Data Assimilation System

SNOTEL
Snow Telemetry

SOI
Southern Oscillation Index

SON
September-October-November

SPoRT
Short-term Prediction Research Transition

SRES
Special Report on Emissions Scenarios

SRP
Salt River Project

SSEBOP
Simplified Surface Energy Balance

SSEBOP ET
Simplified Surface Energy Balance Evapotranspiration

SSP
Societally Significant Pathway

SST
sea surface temperatures

SSW
stratospheric sudden warming

SubX
Subseasonal Experiment

SUMMA
Structure for Unifying Multiple Modeling Alternatives

SVD
singular value decomposition

SW
surface water

SWANN
Snow-Water Artificial Neural Network Modeling System

SWcasts
Southwest Forecasts

SWE
snow water equivalent

SWOT
Surface Water and Ocean Topography

SWS
Statistical Water Supply

Tair
air temperature

Tdew
dew point temperature

TopoWx
Topography Weather (climate dataset)

TVA
Tennessee Valley Authority

UC
Upper Colorado Region (Reclamation)

UCAR
University Corporation for Atmospheric Research

UCBOR
Upper Colorado Bureau of Reclamation

UCRB
Upper Colorado River Basin

UCRC
Upper Colorado River Commission

UCRSFIG
Upper Colorado Region State-Federal Interagency Group

USACE
U.S. Army Corps of Engineers

USBR
U.S. Bureau of Reclamation

USCRN
U.S. Climate Reference Network

USDA
U.S. Department of Agriculture

USGCRP
U.S. Global Change Research Program

USGS
U.S. Geological Survey

USHCN
United States Historical Climatology Network

VIC
Variable Infiltration Capacity (model)

VIIRS
Visible Infrared Imaging Radiometer Suite

VPD
vapor pressure deficit

WBAN
Weather Bureau Army Navy

WCRP
World Climate Research Program

WFO
Weather Forecast Office

WPC
Weather Prediction Center

WRCC
Western Regional Climate Center

WRF
Weather Research and Forecasting

WRF-Hydro
WRF coupled with additional models to represent hydrologic processes

WSF
water supply forecast

WSWC
Western States Water Council

WUCA
Water Utility Climate Alliance

WWA
Western Water Assessment

WWCRA
West-Wide Climate Risk Assessments

WWMPP
Wyoming Weather Modification Pilot Project


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