Perspectives and Guidance for Climate Change Analysis

August 2015

California Department of Water Resources

Climate Change Technical Advisory Group

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California Department of Water Resources (DWR)

Climate Change Technical Advisory Group (CCTAG)

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Technical Information Record

This report represents the preliminary findings from 2012-2015 by DWR's expert external advisory committee, the Climate Change Technical Advisory Group, on global climate model selection appropriate for California water resources, planning for extreme conditions, downscaling, and recommendations for future work.

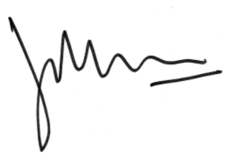
Foreword

Climate change management is a core value of the California Department of Water Resources (DWR), which leads water management adaptation for the state. Moreover, to carry out DWR's mission, incorporation of climate change into DWR's planning, projects, and other activities must be consistent, science-based, and continually improved through an iterative process.

To improve the scientific basis for decisions and enhance the consistency of climate change approaches across all of its programs, DWR empaneled this Climate Change Technical Advisory Group (CCTAG) in 2012. The CCTAG's mission was to advise DWR on the scientific aspects of climate change, its impacts on water resources, the use and creation of planning approaches and analytical tools, and the development of adaptation responses. This 14-member, standing scientific advisory group represents the diverse areas of expertise needed to describe and assess a changing climate. Over the last three years, CCTAG members have worked collaboratively to weigh different alternatives for scenarios and approaches in a changing climate.

This technical information record consolidates the CCTAG's guidance and perspectives from 2012-2015, including interpretation of scientific information produced by the National Climate Assessment and the Fifth Assessment Report of the Intergovernmental Panel on Climate Change. Specific programs that will benefit from this guidance are updates to the California Water Plan, integrated regional water management, flood and drought planning, California's Fourth Assesment of Climate Change, and the Governor's Water Action Plan.

DWR thanks the members of the CCTAG for their time and expertise in completing this report. Actions taken in response to the CCTAG's guidance will efficiently move DWR toward consistency and timeliness in its activities, and will more broadly move California's water sector toward more sustainable management of water and related resources.



John Andrew
Assistant Deputy Director
Sacramento, California
August 21, 2015

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Acronyms and Abbreviations

AIRS	Atmospheric Infrared Sounder
AOGCM/ESM	Atmosphere-Ocean General Circulation Model/Earth System Model
APG	California Climate Adaptation Planning Guide
AR	atmospheric river
AR4	Assessment Report 4
AR5	Assessment Report 5
ARE	atmospheric river event
AWMP	agricultural water management plan
BCCA	Bias-Correction Constructed Analogues
BCSD	Bias-Corrected Spatially Disaggregated
BDCP	Bay Delta Conservation Plan
CA	constructed analogues
CALSIM	California Water Resources Simulation Model
CAT	Climate Action Team
CCTAG	Climate Change Technical Advisory Committee
CEQA	California Environmental Quality Act
cm	centimeters
CMIP	Couple Model Intercomparison Project
CMIP3	Couple Model Intercomparison Project, Phase 3
CMIP5	Coupled Model Intercomparison Project, Phase 5
CNAP	California Nevada Applications Program
CVFPB	Central Valley Flood Protection Board

CWP	California Water Plan
DTR-MMM	mean diurnal temperature range, 1950-1999
DWR	California Department of Water Resources
ECMWF	European Centre for Medium-Range Weather Forecasts
ENSO	El Niño Southern Oscillation
EOF	empirical orthogonal function
ERA-40	ECMWF Re-Analysis 40-km resolution
ESM	Earth System Model
ET	evapotranspiration
GCM	global climate model
GHG	greenhouse gas
HEC-HMS	Hydrologic Engineering Center Hydrologic Modeling Center model
hPa	hectopascal
ifps	inch-foot/second
IPCC AR5	Fifth Assessment Report of the IPCC
IPCC	Intergovernmental Panel on Climate Change
IRWM	integrated regional water management
km	kilometers
LOCA	Localized Constructed Analogues
LW CRE	Long wave Cloud Radiative Effects
MACA	multivariate-adaptive constructed-analogues
Mean-P	mean annual precipitation
Mean-T	mean annual temperature

mi	mile
MM5	Mesoscale Model
MODFLOW	U.S. Geological Survey 3-D groundwater model
NASA	National Aeronautics and Space Administration
NEPA	National Environmental Policy Act
OCAP	Operations Criteria and Plan
P	precipitation
PC	principal component
PR	total precipitation
Q	Quarter (e.g., Q1 = First Quarter)
RCM	regional climate model
RCP	Representative Concentration Pathway
RH	relative humidity
RMSE	root-mean-square error
R-R	rainfall runoff model
RSUT, RLUT	Top of the Atmosphere Reflected Shortwave (S) and Longwave (L) Radiation
RWMG	regional water management group
SAC-SMA	Sacramento Soil Moisture Accounting model
SRES	Special Report on Emissions Scenarios
SW CRE	Shortwave Cloud Radiative Effects
SWP	State Water Project
T	temperature
TAS	surface air temperature

UA	zonal (west-east) winds
USGS	U.S. Geological Survey
UWMP	urban water management plan
VA	meridional (north-south) winds
VIC	variable infiltration capacity
Watts/m^2	Watts per square meter
WEAP	Water Evaluation and Planning model
WG1	Working Group 1 for IPCC
WRF	Weather Research and Forecasting Model
Ws	wind speed
WY	water year
ZG	Geopotential Height

Glossary

AR4. IPPC 4th Climate Change Assessment Report published in 2007.

AR5. IPPC 5th Climate Change Assessment Report published in 2014.

Atmospheric Infrared Sounder (AIRS). Re-analysis data set developed from the AIRS experiment from the National Aeronautics and Space Administration (NASA).

Climate Change Technical Advisory Committee (CCTAG). The CCTAG was formed by the California Department of Water Resources to provide guidance on climate change issues related to water resources planning and management.

Climate change. A change in the state of the climate that can be identified by changes in the mean and/or the variability of its properties (often by using statistical tests), and that persists for an extended period, typically decades or longer.

Climate model. A numerical representation of the climate system based on the physical, chemical, and biological properties of its components, their interactions and feedback processes, and accounting for all or some of its known properties.

Climate projection. A projection of the response of the climate system to emission or concentration scenarios of greenhouse gases and aerosols, or radiative forcing scenarios, often based on simulations by climate models.

Climate variability. Variations in the mean state and other statistics (such as standard deviations, the occurrence of extremes, etc.) of the climate on all spatial and temporal scales beyond that of individual weather events.

Climate. The average weather or the statistical description in terms of the mean and variability of relevant quantities over a period of time, ranging from months to thousands or millions of years.

Delta method. Method using observed historical climate variations as its only example of short-term (days to decades), high-resolution climate variability, which superposes long-term averaged climate changes computed from the global-model outputs onto the high-resolution historical record.

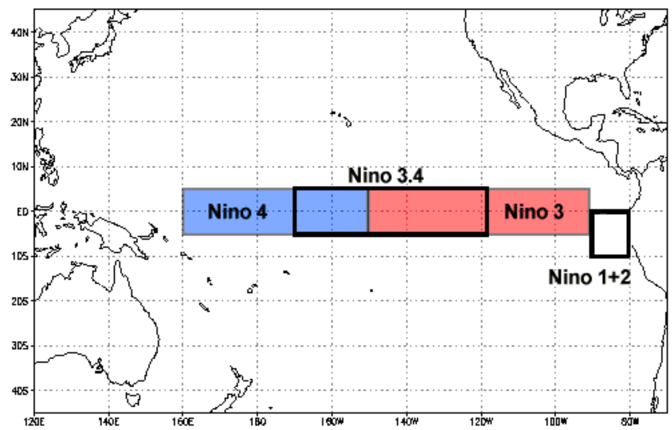
Downscaling. A method that derives local- to regional-scale (10 to 100 km) information from larger-scale models or data analyses.

Drought. A “prolonged absence or marked deficiency of precipitation,” a “deficiency that results in water shortage for some activity or for some group,” or a “period of abnormally dry weather sufficiently prolonged for the lack of precipitation to cause a serious hydrological imbalance.” Agricultural drought relates to moisture deficits in the topmost soil (the root zone) that affect crops. Meteorological drought is mainly a prolonged deficit of precipitation, while hydrologic drought is related to below-normal streamflow and lake and groundwater levels. A megadrought is a long, drawn-out, pervasive drought, lasting much longer than normal, usually a decade or more.

Dynamical downscaling. One of the two main downscaling approaches based on high-resolution 3-dimensional numerical modeling, using a regional or limited-area model solving hydrodynamic equations and thermodynamic equations of the atmosphere, which are focused on the studied/modeled region with initial and 3-dimensional evolving boundary conditions provided by the Atmosphere-Ocean General Circulation Model/Earth System Model (AOGCM/ESM) simulations.

El Niño Southern Oscillation (ENSO). ENSO is a general term used to describe both warm (El Niño) and cool (La Niña) ocean-atmosphere events in the tropical Pacific, as well as the Southern Oscillation the atmospheric component of these phenomena. El Niño and La Niña occur when sea surface temperatures in the Pacific Ocean near the equator and the west coast of South America, called the Niño 3.4 region, are unusually warm (El Niño) or cold (La Niña) for an extended period of time.

El Niño Southern Oscillation



Source: NOAA: https://www.ncdc.noaa.gov/teleconnections/enso/indicators/sst.php

ENSO-P. Correlation of winter precipitation with Nino 3.4 index, 1901-1999.

ERA-40. ECMWF Re-Analysis 40-km resolution data set of the global atmosphere and surface conditions for 45-years, over the period from September 1957 through August 2002, conducted by European Centre for Medium-Range Weather Forecasts.

Global climate model (GCM). Computer model that simulates global climate and ocean patterns.

Greenhouse gases (GHG). Those gaseous constituents of the atmosphere, both natural and anthropogenic, which absorb and emit radiation at specific wavelengths within the spectrum of thermal infrared radiation emitted by the earth's surface, the atmosphere itself, and by clouds.

Intergovernmental Panel on Climate Change (IPCC). Scientific panel overseen by the United Nations, which investigates the global impacts of climate change.

Parameterizations. Simple mathematical rules that represent features (e.g., convective cloud formation) too small to be resolved by the model.

Precip (or precipitation) duration. An approximation of the length of time for accumulation of precipitation.

Precip (or precipitation) intensity. An approximation of the rate of fall or the rate of accumulation of precipitation.

Projection. Any description of the future and the pathway leading to it; a more specific interpretation has been attached to the term “climate projection” by the IPCC when referring to model-derived estimates of future climate. See also Climate Projection.

Reanalysis. Atmospheric and oceanic analyses of temperature, wind, current, and other meteorological and oceanographic quantities created by processing past meteorological and oceanographic data by using fixed, state-of-the-art weather forecasting models and data assimilation techniques.

Reconstruction. The use of climate indicators to help determine climates (generally of the past).

Reoperation. See System Reoperation.

Representative Concentration Pathway (RCP). Future greenhouse gas scenarios used in the IPPC 5th Climate Change Assessment. The number after RCP (e.g., RCP4.5 and RCP8.5) is the increase in radiative forcing at the end of the century in W/m^2 (+4.5 W/m^2 and +8.5 W/m^2). The RCP scenarios replaced the SRES scenarios.

Scenario. A plausible and often simplified representation of the future climate, based on an internally consistent set of climatological relationships that has been constructed for explicit use in investigating the potential consequences of anthropogenic climate change, often serving as input to impact models.

Simulation. Computerized model runs that represent interactions of the atmosphere, oceans, land surface, and ice; designed to project future temperature changes resulting from increases in atmospheric concentrations of greenhouse gases.

Special Report on Emissions Scenarios (SRES). Future greenhouse gas scenarios used in the IPCC 3rd and 4th Climate Change Assessment Reports. SRESB1 is a lower future greenhouse gas emissions scenario than SRESA2. The SRES scenarios were replaced by the RCP scenarios.

Statistical downscaling. Methods for developing statistical relationships that link the large-scale atmospheric variables with local/regional climate variables.

Streamflow. The amount of water flowing in a river.

Stress tests. Methods to characterize the range of extremes, such as drought or flood; assess vulnerability to these extremes; develop scenario-based analyses that assess system response; and determine ways to increase resilience to these events.

System Reoperation. California's water supply and flood management infrastructure is physically interconnected, but is not as well integrated as it could be. DWR, in cooperation with other State and federal agencies, local water districts, groundwater managers, and other stakeholders, is investigating potential strategies to take advantage of the physical interconnections between flood protection and water supply infrastructure, while operating the system in a coordinated manner to provide additional benefits.

Teleconnection. A connection between climate variations over widely separated parts of the world. In physical terms, teleconnections are often a consequence of large-scale wave motions, whereby energy is transferred from source regions along preferred paths in the atmosphere.

Water year (WY). The water year runs from October 1st of the previous year to September 30th of that year. For example, water year 2014 is October 1, 2013, to September 30, 2014.

Metric Conversion Factors

Quantity	To Convert from Metric Unit	To Customary Unit	Multiply Metric Unit By	To Convert to Metric Unit Multiply Customary Unit By
Length	millimeters (mm)	inches (in)	0.03937	25.4
	centimeters (cm) for snow depth	inches (in)	0.3937	2.54
	meters (m)	feet (ft)	3.2808	0.3048
	kilometers (km)	miles (mi)	0.62139	1.6093
Area	square millimeters (mm2)	square inches (in2)	0.00155	645.16
	square meters (m2)	square feet (ft2)	10.764	0.092903
	hectares (ha)	acres (ac)	2.4710	0.40469
	square kilometers (km2)	square miles (mi2)	0.3861	2.590
Volume	liters (L)	gallons (gal)	0.26417	3.7854
	megaliters (ML)	million gallons (10)	0.26417	3.7854
	cubic meters (m3)	cubic feet (ft3)	35.315	0.028317
	cubic meters (m3)	cubic yards (yd3)	1.308	0.76455
	cubic dekameters (dam3)	acre-feet (af)	0.8107	1.2335
Flow	cubic meters per second (m3/s)	cubic feet per second (ft3/s)	35.315	0.028317
	liters per minute (L/mn)	gallons per minute (gal/mn)	0.26417	3.7854
	liters per day (L/day)	gallons per day (gal/day)	0.26417	3.7854
	megaliters per day (ML/day)	million gallons per day (mgd)	0.26417	3.7854
	cubic dekameters per day (dam3/day)	acre-feet per day (af/day)	0.8107	1.2335
Mass	kilograms (kg)	pounds (lbs)	2.2046	0.45359
	megagrams (Mg)	tons (short, 2,000 lb.)	1.1023	0.90718
Velocity	meters per second (m/s)	feet per second (ft/s)	3.2808	0.3048
Power	kilowatts (kW)	horsepower (hp)	1.3405	0.746
Pressure	kilopascals (kPa)	pounds per square inch (psi)	0.14505	6.8948
	kilopascals (kPa)	feet head of water	0.32456	2.989
Specific capacity	liters per minute per meter drawdown	gallons per minute per foot drawdown	0.08052	12.419
Concentration	milligrams per liter (mg/L)	parts per million (ppm)	1.0	1.0
Electric conductivity	microsiemens per centimeter (µS/cm)	micromhos per centimeter (µmhos/cm)	1.0	1.0
Temperature	degrees Celsius (ºC)	degrees Fahrenheit (ºF)	(1.8XºC)+32	0.56(ºF-32)

Supplemental Metric Conversion Factors

Quantity	To Convert from Metric Unit	To Customary Unit	Multiply Metric Unit By	To Convert to Metric Unit Multiply Customary Unit By
Flux	m^2/sec	in-ft/sec (ifps)	129.87	7.7 X 10^{-3}
Heat Flux Density	Watt/m^2 (W/m^2)	W/sq ft	9.290 X 10^{-2}	10.76
Pressure	kgf/m^2	hPa	9.8 X 10^{-2}	10.19

Notes: The Pressure entry in the “To Convert from Metric Unit” column is “kilogram force per square meter,” which explains the use of the letter “f”.

Executive Summary

California’s uniquely variable climate is both attraction and challenge to its 38.5 million residents. The state’s varied geography and location on the west coast of North America bring a rare range of climates in close proximity. Planning for California’s water future must recognize and address a robustly dynamic climate now affected by human activities of the post-industrial age, and we are just beginning to understand those impacts.

Wild swings in California’s precipitation patterns are legendary, challenging water managers to the extreme. Those swings provided the historical motivation for developing the state’s complex water storage and conveyance infrastructure. Today, California’s world-renowned system of dams, diversions, pumps, and canals collect, store, then distribute water to match the timing of supply and demand across the state.

California's water managers face a climate that changes and is changing as a result of both natural and anthropogenic influences. In some settings and for some variables, California’s natural climate variability still dominates anthropogenic influences and will continue to do so for the foreseeable future. In other cases, anthropogenic influences are already evident in important aspects of California's climate. Much research is still required to unravel this tangled web of atmospheric interactions. In any case, California water planning under a changing climate needs to recognize that the causes of variations and changes include both anthropogenic and natural drivers.

This technical information record summarizes the scientific and technical guidance and perspectives of the California Department of Water Resources’ (DWR’s) Climate Change Technical Advisory Group (CCTAG) on the use of climate models and associated technical tools for water resource planning. DWR values the work of the members of the CCTAG and will consider this advice as it moves forward in developing specific actions.

DWR empaneled this CCTAG in February 2012 to advise DWR on the scientific aspects of climate change, its impacts on water resources, the use of planning approaches and analytical tools, and the development of adaptation responses. DWR requested specific assistance with developing:

- A set of future climate scenarios and analysis procedures appropriate for DWR planning.
- An approach to extreme climate change scenarios to provide “stress tests.”
- Interim guidance on modeling extreme weather events that cause flooding (time permitting within the tenure of the CCTAG).

Introduction

As DWR and the state’s other water agencies plan for future water resource needs, climate change necessitates a move away from traditional water resources planning approaches that assume our future climate will be the same as our recently observed climate. New approaches are needed that explore shifts in climatic conditions, both natural and human-made, and other uncertainties about the future.

To improve the scientific basis for decisions and enhance the consistency of approach across all DWR programs, DWR identified several areas where additional guidance was requested.

- **Global Climate Model (GCM) Selection or Sampling.** There are more than 60 global climate models (GCMs) currently used by the Intergovernmental Panel on Climate Change (IPCC) in its Fifth Assessment Report. The full suite of available climate simulations is too large to use for detailed water resource evaluations. Guidance is needed on how to reduce the number of simulations to a manageable total for State and local application.
- **Planning for Extreme Conditions.** Identifying how climate change might alter extreme conditions in the future goes beyond the expertise of most water managers. DWR requested advice from the CCTAG on how to assess extreme climate conditions that California may face in the future.
- **Downscaling.** Modeling global climate is an enormous computational challenge. Even with today's powerful computers, computational compromises are required that result in coarse resolutions that do not meet the needs at State and local scales. DWR requested advice on the translation of GCM data to scales more appropriate for water resource system analysis in California.
- **Recommendations for Future Work.** DWR requested that the CCTAG recommend future improvements to climate change analyses for California, along with recommendations for improving climate change analysis of regional and local water resources programs not directly implemented by DWR, but which are strongly influenced by DWR.

Global Climate Model Selection or Sampling

Using an ensemble or group of several simulations from different GCMs for planning studies is the current best practice by which to consider the range and uncertainty of future climate projections. GCMs provide simulations used to investigate possible future climate variability and changes. Although observations of past climate from instrumental records and proxy indicators, such as tree rings, are also valuable guides, simulations from GCMs are the primary means of looking forward in a quantitative fashion. Nonetheless, GCM simulations are not perfect forecasts. The models are affected by different forms of uncertainty, including uncertainties in atmospheric components, such as aerosols and greenhouse gases; in the model representation of the real climate system; and in results ensuing from natural variability.

Simulations from more than 60 GCMs have been contributed to the IPCC Coupled Model Inter-comparison Project Phase 5 (CMIP5) archive. The large number of simulations is a multiple of the number of GCMs modeling different forcing scenarios, known as Representative Concentration Pathways or "RCPs." Each RCP represents a different combination of possible future concentrations of atmospheric aerosols and greenhouse gases.

The large variety of CMIP5 model simulations provides a valuable resource by which to probe possible future climate change. On the other hand, the sheer size of the simulation ensemble is intractable to many users and decision-makers. On account of differences in model performance resulting from assumptions, approximations, and formulations, each model has strengths and weakness. Some models simulate certain climate features better than others.

To identify a subset of the "better" GCMs for developing assessments and plans for California water resource issues, as well as to develop a more manageable climate change ensemble, a 3-step model selection procedure was used. This procedure was based on evaluations of GCM historical performance at the global scale and across the southwestern United States, and to address specific needs for California water resources planning.

Key performance features deemed by CCTAG as important to California include correlation and variance of mean seasonal spatial patterns, amplitude of seasonal cycle, diurnal temperature range, annual- to decadal-scale variance, long-term persistence, and regional teleconnections to El Niño Southern Oscillation.

The recommended subset includes 10 GCMs that produce reasonably realistic simulations of global, regional, and California-specific climate features. The CCTAG judged these GCMs as currently the most suitable for California climate and water resource assessment and planning purposes.

Planning for Extreme Conditions

The hydroclimate of California is anything but stable and predictable. Data suggest that California's climate persistently drifts from wet to dry and wet again, yet remains in a given state for decades or more at a time. Most of California's observed hydrometeorological data only cover the period where the state's hydroclimate transitioned from a very dry to very wet conditions during the last 60-70 years of the 20th century. Because most observation records miss a major component of the California's wet/dry cycle, analyses and water management strategies that use these records may be seriously compromised.

Research also suggests that California's annual precipitation swings are strongly linked to the number of atmospheric river events reaching California. Drought conditions prevail when the numbers are persistently low or the events too weak. Conversely, a robust pattern of atmospheric river events promotes flooding.

Extreme events challenge water resource systems and managers and provide a measuring stick of how well systems are designed for their intended purposes. The CCTAG acknowledges that climate change impacts on extreme events remains uncertain. Given the imperfect knowledge of hydroclimate processes and their response to climate change, stress tests built through constructed extreme, yet plausible, events offer a vehicle to assess extremes in a planning process while enabling changes to those tests as knowledge gaps are filled. DWR planning processes can use this framework as part of the climate change analyses.

Understanding underlying atmospheric and hydrologic processes is an important element in understanding climate change impacts on the hydrologic cycle, including the cycle's extremes. The integration of these processes that yields a flood or drought is complex. CCTAG supports continued efforts to identify knowledge gaps and pursue studies to address such gaps.

Finally, the CCTAG recognizes that variability across different space and time scales, including decadal-scale variability, is an important part of the climate system that may not be adequately understood or captured in the observed historical record. Its incorporation into stress tests and extremes has a clear tie to evaluating water system shortages resulting from droughts of various magnitudes and durations. Further investigation and discussion should be included in future efforts.

Downscaling

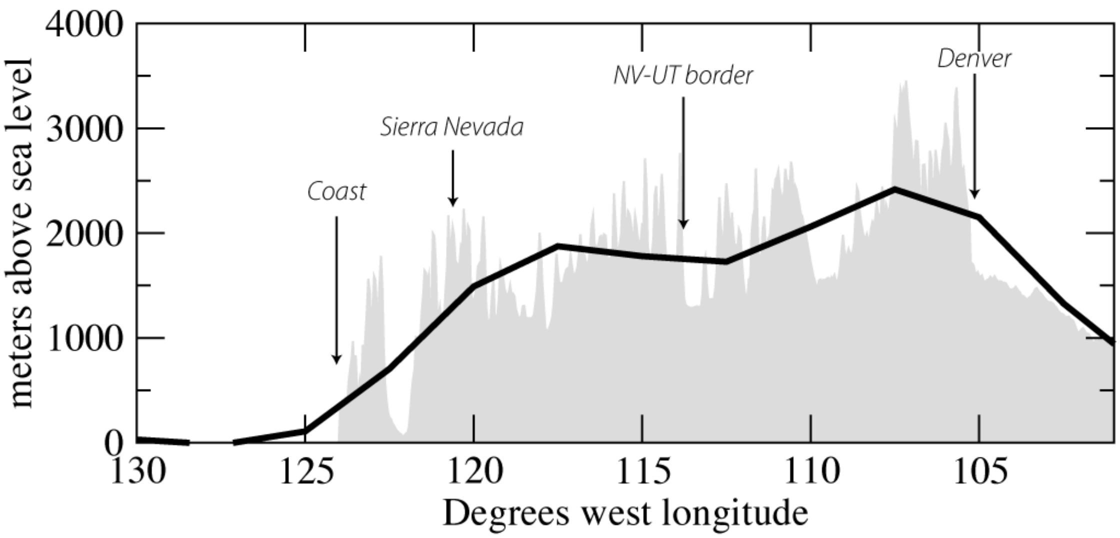
GCM climate-change projections provide the raw materials for most assessments of vulnerabilities and responses to climate change by DWR and others. Today, GCM projections are typically made by simulating climatic response to different RCPs.

GCMs represent the climate as discrete grids and layers that span the globe, with the geographic distribution of grid-cell centers typically separated by about 1 degree to more than 2.5 degrees of latitude and longitude. One degree of latitude and longitude in California equals approximately 100 kilometers (62 miles), or about the distance from Sacramento to Berkeley. A single 2.5-degree grid cell spans the distance from San Francisco to Lake Tahoe across two mountain ranges and the Central Valley.

At 2.5-degree resolution, the Sierra Nevada mountains do not appear as a separate mountain range from the great western North American mountain belt, the Coast Ranges are nonexistent, and the highest peak along the latitude of Red Bluff only rises to about 2500 meters (8202 feet) above sea level. Average elevations at each 2.5-degree by 2.5-degree grid cell along 40-degree-north latitude are shown by the heavy black line in Figure ES-1, as an example of topographic smoothing that occurs in global-model-scale outputs. Land-surface slopes and land-water contrasts are almost entirely muted. No river catchment in California spans more than a few of the GCM grid cells, and most are much smaller than any one grid cell.

In contrast, the gray background in Figure ES-1 represents a more realistic elevation profile along 40 degrees north. The complex natural topographic climate influences of the Coast Ranges, the Central Valley, and the Sierra Nevada mountains are almost entirely lost in the 2.5-degree resolution GCMs.

Figure ES-1 Cross-Section Showing Elevations along 40º North



Notes:

Average elevations at each 2.5ºx2.5º grid cell along 40ºN latitude (shown as heavy black line) as an example of topographic smoothing that occurs in global-model-scale fields and outputs. Grey background represents the actual elevation profile along 40ºN. This figure also appears in Chapter 4, under the title "Average Elevations at Each 2.5º x 2.5º Grid Cell in the NCEP-NCAR Reanalysis Fields for Transect at 40 Degrees North Latitude."

Climate projections at this coarse resolution offer little immediate information about the spatial details of climate differences and variabilities that drive most of California's watersheds. As a consequence, various procedures collectively referred to as "downscaling" are applied to translate GCM-scale output for use in local-to-small-scale regional applications.

Downscaling has been pursued in California by using both statistical and dynamical methods. Dynamical downscaling employs GCM outputs as initial and boundary conditions for simulations using high-resolution models of local-to-regional climate. Dynamical downscaling uses the same or similar numerical solutions of the 3-dimensional hydrodynamic and thermodynamic equations of the atmosphere as the GCMs, but with much greater detail. These solutions combine the initial and boundary conditions supplied by the GCMs with the RCPs to project global climate to watershed-scale processes.

Statistical downscaling assumes or derives statistical relationships between historical high-resolution observations of climate variables and GCM outputs. Then, these historically derived relationships are applied to other past or future outputs of the same GCM to estimate the high-resolution details of future climate. Statistical downscaling has the advantage of downscaled products being readily available for a large number of climate-change scenarios from different global models and under a variety of different assumptions.

The downscaling process adds further uncertainty to climate analyses. Dynamical downscaling is imperfect in ways similar to ways GCMs are imperfect representations of climate. Historical relationships between GCM output and observations that underpin statistical downscaling are not exact and may not be preserved in future decades. Both dynamical and statistical downscaling methods introduce biases that must be removed to produce realistic output.

DWR's needs for high spatial resolution climate-change analyses far outstrip the resolutions of current GCMs and will probably continue to outstrip available resolutions in the time ahead. By necessity, DWR will rely on downscaling as an integral part of its climate-change analyses for the foreseeable future. The CCTAG has provided these key points:

- Statistical-downscaled products are acceptable to meet immediate needs, as well as for continuity, consistency with efforts by agencies other than DWR, and convenience. Nonetheless, either new statistical methods or, preferably, dynamical downscaling will be needed to address many issues that DWR is likely to face in the future.
- DWR should design and/or support an inter-comparison of downscaling methods and sources that reflects its particular applications and needs.
- DWR should prepare for a future that will likely use dynamical downscaling methods by:
    - Joining with research efforts that are improving the accuracy of high-resolution dynamical models.
    - Preparing its own watershed-scale models and analyses to use the more highly resolved and multivariate results that dynamical models will yield.
- DWR should develop an appraisal and plan for the readiness of the observation networks that will underpin its climate-change activities, including downscaling of climate-change scenarios.

Recommendations for Future Work

As noted earlier, planning for California's water future must recognize and address a robustly dynamic climate now affected by human activities of the post-industrial age. Much work remains. CCTAG's recommendations for future work concerning climate change in larger-scale water resources planning include the following activities:

- Screen viable water-resources planning options.
- Provide centralized information and support for managers.
    - Establish a database and information system.
    - Establish climate competency and training modules to apply the latest climate science.
    - Develop guidance and tools for communicating and managing uncertainty in water resources planning and management.
    - Establish a process for assessing the strengths, gaps, and suitability of planning and management models relative to planning and management needs.
    - Continuously monitor developments in climate science and methodologies, and share results.
    - Coordinate DWR climate-change planning with other State agency, Southwest Region, and national activities.
- Establish programs to support research in water resources planning and management under climate uncertainty and trends.
- Develop guidance and incentives for better monitoring of climate-change impacts.

There are a number of water-resource-related planning activities currently performed by local or regional resource managers that DWR supports, provides context for, or influences. These management plans include, but are not limited to, urban water, agricultural water, groundwater, habitat conservation, water supply, hazard mitigation, stormwater, and flood.

Local agencies have different levels of resources and expertise. Some agencies commission GCM-downscaling studies for long-range planning, and some integrated regional water management plans have incorporated climate change vulnerabilities assessments. Even so, many regional and local planning efforts lack the resources and expertise to commission studies to get location-specific answers.

The CCTAG recommends that DWR develop plans and outreach efforts to support local and regional planning agencies in addressing the following questions:

- How can model outputs be used to assess climate risks on water resources? For example:
    - What duration and intensity of drought conditions should communities prepare for?
    - What frequency and intensity of storms, and extent of flooding, should communities prepare for?
    - How will climate change affect groundwater recharge, stream flows, water temperatures, and fisheries?
    - Does the uncertainty in projections warrant re-estimation of safety factors for the development of water infrastructure with a long lifetime?
- What foundational knowledge is critical before applying climate model products? When using climate model products is not appropriate or feasible, what simpler methods can be used to forecast future climate conditions?
- Do projected climatic extremes and associated impacts warrant the examination of institutional issues associated with established guidelines for water managers and with interagency cooperation?
- What are appropriate impact assessment uses for GCMs and RCMs, and how could they best be incorporated into local and regional planning?

- How can an intercomparison of downscaling methods and sources be designed or supported to reflect particular applications and needs?
- How can an appraisal and plan be developed for the readiness of the networks of observations that underpin climate-change downscaling activities?
- What are the most appropriate methods and hydrologic models for converting GCM and downscaled data into hydrologic and water resources management information relevant to regional and local water resources planning?
- How can regional and local water managers access these models?
- Where can regional and local planners seek help when questions arise in application of these models?
- What forum or processes exist for regional and local water managers to support continuous learning and improvements for keeping up with the latest science and with model applications?
- How can adaptation options that are proactive and increase resilience to climate change impacts be identified and assessed?

This report represents the findings and recommendations of the members of the CCTAG. DWR has not decided or committed to follow the findings or recommendations in any particular plan, project, or activity undertaken by DWR.

Chapter 1. Introduction

Understanding climate change is a two-fold challenge. First, the underlying rhythms of pre-industrial climate must be decoded, and then it must be determined how human activities are changing those rhythms. Variability and change — particularly in the form of inter-annual fluctuations in precipitation — have been a fundamental characteristic of California's climate for thousands of years (see Box 1-1). But more recently, human activities have changed the underlying atmospheric composition of the earth, resulting in climate variability and change that go beyond California's natural rhythms. As anthropogenic climate change is added to California's natural climate variability, weather events and climatic conditions that historically would have been extremely rare may become more common, previously unprecedented weather and climate events may begin to occur more routinely, and historical experience becomes less relevant when planning for the future.

Climate changes are manifesting themselves in ways that put stress on water resources throughout the state: higher sea levels; loss of snowpack; earlier runoff; increased water demands; larger storm flows; and longer, more severe droughts. DWR performs a number of planning and analysis activities each year to explore expected changes in the future climate, and to understand potential impacts on water-resources system performance and management options. Further, DWR supports several local and regional water-management activities that require analysis of future climatological conditions. As DWR and the state's other water agencies plan for future water resource needs, climate change necessitates a move away from traditional water-resources planning approaches based on the principle of stationarity, and a move to new approaches that explore shifts in climatic conditions and other uncertainties about the future. Along with new approaches to planning, additional information and assumptions about future conditions must be incorporated into analyses.

This report summarizes the perspectives and guidance of the California Department of Water Resources' (DWR's) Climate Change Technical Advisory Group (CCTAG) regarding the use of climate models and associated technical tools for use in water resource planning. DWR empaneled this CCTAG to provide expert advice on the scientific aspects of climate change, its impacts on water resources, the use and creation of planning approaches and analytical tools, and the development of adaptation responses. DWR requested specific assistance with developing:

- A set of future climate scenarios and analysis procedures appropriate for DWR's planning activities.
- An approach to extreme climate-change scenarios to provide "stress tests."
- Interim guidance on modeling extreme weather events that cause flooding (time permitting, within the tenure of the CCTAG).

This report summarizes the discussions and analysis conducted by DWR staff and CCTAG members from February 2012 through March 2015. CCTAG membership and activities are posted here: http://www.water.ca.gov/climatechange/cctag.cfm.

Box 1-1 California Climate

Home to more than 38 million people, California's uniquely variable climate is both an attraction and a challenge to life in the state. Spanning nearly 10 degrees latitude and 10 degrees longitude, California stretches from the hot, dry desert in the southeast corner to a mild, wet clime in the northwest corner, with mountain ranges, alpine meadows, coastal plains, and a broad central valley in between. Within its 158,693-square-mile (411,013-square-kilometer) domain can be found the lowest elevation in the continental United States, at 276 feet (84 meters [m]) below sea level in Death Valley, and the highest elevation at Mt. Whitney's 14,505-foot (4421-m) peak.

Two major mountain features, the Coast Ranges and the Sierra Nevada, dramatically shape California's rainfall patterns. The Coast Ranges parallels the coast, from the Oregon border to Los Angeles, with crests generally no more than 50 miles (80 kilometers [km]) inland. Approximately 150 miles (241 km) east, beyond the Great Central Valley, the Sierra Nevada mountain range parallels the Coast Ranges and the coastline, and includes a dozen peaks above 14,000 feet (4,267 m). Steep west-facing slopes help squeeze precipitation from moisture-laden storms arriving from their long journey across the Pacific Ocean.

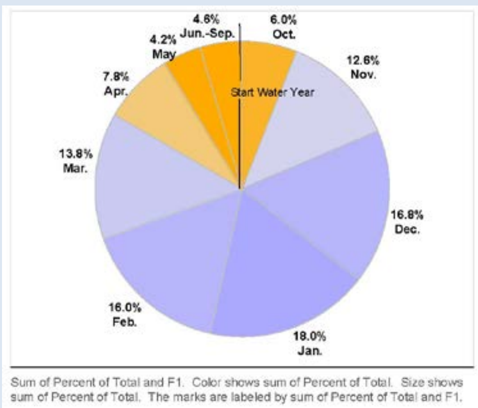
At higher elevations, moisture falls mostly as snow. The annual accumulation of snow forms California's most important reservoir of water, which is needed to help quench a thirsty state during hot, dry summers.

California's varied geography and location on the west coast of North America bring a rare range of climate types in close proximity. Most of California's precipitation falls in northern portions of the state. Desert areas in Southern California see less than 4 inches (10 centimeters [cm]) of precipitation annually, while some locations in the north average more than 100 inches (254 cm) per year.

In addition to extreme variations in average annual precipitation across the state, seasonal variability is extreme. About half of Northern California's precipitation falls within three months — December, January, and February. (See Figure 1-1.) November and March bring the total to about two-thirds. The remaining precipitation occurs during the seven much-drier months of the year.

Figure 1-1 Annual Distribution of Northern California Precipitation

Data courtesy of Maury Roos, DWR



Wild swings in California's precipitation patterns from year to year are legendary. In Sacramento's 164-year rainfall record, annual totals range from less than 8 inches (20 cm) to more than 45 inches (114 cm). Such variations challenge water managers in the extreme and were the driving force behind the development of the state's complex water storage and conveyance infrastructure. Today, a world-renowned system of dams, diversions, pumps, and canals collect and distribute water to match the timing of supply and demand across the state.

Recently, a new source of variability in California's precipitation has become apparent. Information from the state's longest observed precipitation records and insights derived from thousand-year records of tree-ring data strongly suggest a dynamic climate that continuously drifts between wet and dry regimes lasting decades at a time. Long-term precipitation shifts of 30-40 percent have been observed. Furthermore, these data suggest that California's climate can transition from wet to dry or dry to wet within a few decades, well within common water-resource planning horizons.

California water managers face extraordinary challenges. Most of California's water is derived from the northern half of the state, while most of the demand for water occurs in the south. Seasonal, annual, and decadal precipitation variability compounds the challenge. If that were not enough, anthropogenically driven changes in the projected amount, distribution, timing, and form of precipitation add new layers of immense complexity to California's water management challenge.

Since at least 2006, DWR has been using a variety of approaches to explore how climate changes may affect future water resource conditions in California (described below). Working to improve the scientific basis for decisions made in these types of analyses, as well as in the consistency of data and approach across all DWR programs, DWR identified for the CCTAG several areas in which additional science-based guidance would be helpful.

- **Model Selection or Sampling** (Chapter 2). Currently, more than 60 global climate models (GCMs) are being used by the Intergovernmental Panel on Climate Change in its Fifth Assessment Report. These models have been run with as many as four greenhouse-gas emissions scenarios (otherwise known as Representative Concentration Pathways or RCPs). Additionally, each model may have been run with several initial conditions. Each combination of model, RCP, and initial conditions represents a unique simulation of the climate system. The full suite of climate simulations (all models, RCPs, and initial conditions) would be too large to use for detailed water resource evaluations. Thus, selection, sampling, or averaging of the suite of climate simulations must be done to reduce the number of simulations to a manageable number. This process requires a level of understanding and technical knowledge of the climate models and simulation methodologies that goes beyond the expertise of most water managers.
- **Planning for Extreme Conditions** (Chapter 3). Evaluating a water system's performance and vulnerability during extreme or prolonged droughts or very large flooding events is an important part of water planning throughout California. Identifying how climate change might alter what those extreme conditions look like in the future goes beyond the expertise of most water managers; accordingly, DWR has requested perspectives and guidance from the CCTAG on the development and analysis of extreme climate conditions.
- **Downscaling** (Chapter 4). DWR has requested perspectives and guidance on the use of various approaches to downscaling GCM data at 100- to 200-kilometer (km) (62.14- to 124.27-mile) grid spacing to scales that are more appropriate for water resource system analysis (<12 km) (<7.5 miles). Additionally, DWR has requested perspectives and guidance on the ways in which historical observational data for both climate and stream flow can best be used in climate change analysis (i.e., under what circumstances or for what purposes would it be most appropriate to use historical data as a baseline upon which climate change trends could be mapped, as opposed to using GCM/hydrologic model projections directly).
- **Recommendations for Future Work** (Chapter 5). DWR has requested that CCTAG provide future recommendations for climate change analyses, which go beyond the perspectives and guidance provided throughout the report. In addition, DWR has requested perspectives and guidance from the CCTAG on improving climate change analysis of regional and local water resources programs that are not directly implemented by DWR, but which are strongly influenced by DWR.

Perspectives and guidance provided by the CCTAG to DWR regarding the preceding four subject areas are discussed in Chapters 2 through 5 of this report. Each of the four chapters provides information about a different aspect of climate change analysis.

Chapters 2 and 3 cover the range of potential future conditions that DWR may need to consider when planning for the future. Chapter 2 focuses on the use of GCMs that provide projections of future climate conditions going out to 2100. These models were designed to provide information about future trends in temperature, precipitation, and other climate metrics. The perspectives and guidance in Chapter 2 should be useful for deciding which GCMs would be most effective in evaluating these aspects of future climate. GCMs may be less well suited to simulating smaller-scale or shorter-duration climate events, such as storms that cause flooding. On their own, GCMs may also be insufficient for exploring the inter-annual and seasonal variability in precipitation that can result during droughts. Chapter 3 provides additional information for DWR to consider when evaluating these types of potential climate changes.

Chapter 4 provides perspectives and guidance on downscaling. Downscaling will almost always be required for water resource analysis when using GCMs because of the GCMs' coarse spatial scale. Downscaling may also be required for using other types of data for extreme events analysis described in Chapter 3.

Chapter 5 provides CCTAG's recommendations for future activities DWR might undertake to improve their treatment of climate change analysis and the support that they provide to water management entities throughout the state.

This report represents the findings and recommendations of the members of the CCTAG. DWR has not decided or committed to follow the findings or recommendations in any particular plan, project, or activity undertaken by DWR.

Past Activities and Modeling Approaches

In 2010, DWR performed a comprehensive survey and evaluation of its past climate change analyses and published the report *Climate Change Characterization and Analysis in California Water Resource Planning Studies* (Khan and Schwarz 2010). Thirteen different studies were identified that had been undertaken or were being undertaken between 2006 and 2010, highlighting DWR's involvement in a number of planning and analytical activities that required analysis of future conditions. Table 1-1 shows the range of climate-change scenarios used by DWR during this period; see the Glossary for definitions of terms). These activities were categorized into two distinct groups: (1) general planning studies that evaluated future conditions for the purposes of identifying coming changes or exploring potential risks (e.g., California Water Plan updates, general climate change impacts reports); and (2) project-level analyses conducted to evaluate a specific project or series of projects (e.g., environmental impact reports, hydroelectric relicensing studies). These two different types of activities had very different purposes, objectives, and constraints, and information from the two types of activities was used in different ways. Given the differences in the types of activities, it was not surprising to find among projects some differences in the way climate change characterization and analysis were undertaken. Then again, it was found that across the 13 activities, there was almost no consistency in the way climate information was incorporated into the analysis. Different models were used, different emissions scenarios were used, and different approaches were taken with respect to projected climatic changes. In some cases, changes were mapped onto historical data while in other studies, the projected climate changes were used to directly drive models of streamflow. The 13 different studies took 13 different approaches to characterizing and analyzing future climate conditions in California. These findings spurred DWR to work toward greater standardization of analytical approaches, with the goal of improving consistency of message across DWR documents, streamlining decision-making and document review, and increasing the potential for inter-comparisons with other DWR reports and compatibility with local and regional water planning efforts.

DWR Planning Applications

The perspectives and guidance in this report will be used to inform DWR's decisions on an array of specific types of applications, including future updates of the California Water Plan beyond 2013, State Water Project (SWP) delivery reliability reports, environmental impact reports as required by the California Environmental Quality Act, federal feasibility reports in which DWR participates, system reoperation studies, and other analyses of potential future conditions and management options. While all of these types of studies are performed by DWR, they also provide critical information used in decision-making at the State, federal, and local levels. For example, State Water Project delivery reliability reports are used by many integrated regional water management planning groups and urban water management planning agencies to inform projections of future SWP reliability for their planning (Conrad 2012, 2013). Table 1-2 provides a list of DWR's primary planning activities and a summary of how they are used by DWR.

Each of the study types listed in Table 1-2 provides different levels of climate change information; performs different types of analyses; and typically relies on hydrologic models, water system models, and specific resource impact models to analyze the effects of climate changes. Table 1-3 summarizes the primary water management modeling tools used for these types of planning studies and the climate data used to drive the models. This table highlights a wide range of analyses that may be performed with only a limited set of necessary model types. The number of climate variables currently used to drive these models is even more limited. Additional climate variables may have important effects on outputs of interest, but current modeling capacity does not allow consideration of other variables. Appendix A provides additional information on California's water system.

Table 1-1 **Climate Scenarios DWR Used Between 2006 and 2010**

CAT Scenarios	Ref. Year	Emissions Scenarios[a]	Adjusted Climatology	Unadjusted Climatology
Parallel Climate Model; National Center for Atmospheric Research	2000	A2, B1	NO	YES
Geophysical Dynamics Laboratory model version 2.1; US Dept. of Commerce/National Oceanic and Atmospheric Administration (NOAA)/Geophysical Fluid Dynamics Laboratory (GFDL)	2006	A2, B1	NO	YES
Community Climate System Model; National Center for Atmospheric Research (NCAR)	2006	A2, B1	NO	YES
Max Planck Institute (MPI) for Meteorology, Germany	2006	A2, B1	NO	YES
Center for Climate System Research (University of Tokyo); National Institute for Environmental Studies; and Frontier Research Center for Global Change (JAMSTEC), Japan	2004	A2, B1	NO	YES
Meteo-France/Centre National de Recherches Meteorologiques (CNRM), France	2005	A2, B1	NO	YES
Bay Delta Conservation Plan Ensemble Scenarios				
Q1-10nn (drier, more warming)	2010	ensemble A2, B1, A1b	YES	YES
Q2-10nn (drier, less warming)	2010	ensemble A2, B1, A1b	YES	YES
Q3-10nn (wetter, more warming)	2010	ensemble A2, B1, A1b	YES	YES
Q4-10nn (wetter, less warming)	2010	ensemble A2, B1, A1b	YES	YES
Q5-25th-75th percentile ensemble (approx. 25-38 members)	2010	ensemble A2, B1, A1b	YES	YES
OCAP Scenarios				
Projection 1 (wetter, less warming)-MRI CGCM2.3.2a		A2 sim#5	No	Yes
Projection 2 (wetter, more warming)-NCAR CCSM3.0		A1b sim#3	No	Yes
Projection 3 (drier, less warming)-MRI CGCM2.3.2a		A2 sim#2	No	Yes
Projection 4 (drier, more warming)-UKMO HADCM3		A2 sim#1	No	Yes

Notes:

10nn = ensemble based on 10 nearest neighbor method; CAT = Climate Action Team; OCAP = Operations Criteria and Plan; Q = Quarter (e.g., Q1 = First Quarter)

All model acronyms are defined by the Intergovernmental Panel on Climate Change here: http://www.ipcc.ch/.

[a]"Scenarios," in this context, is defined as a simulation of future conditions based on a single Global Climate Model (GCM) projection or the ensemble average of multiple GCM projections.

Table 1-2 Climate Change Analysis in DWR Planning Activities

Study Type	Level of Detail	Time Horizon	Spatial Coverage	Notes	Example
General Planning Studies	Policy Level/General	30-100 years	Typically large (statewide/Central Valley water systems)	Not specific to climate change; ability to explore multiple future projections may vary. High level and broad analysis, usually not directly connected to specific decision-making. Designed to inform the legislature, public, or local/regional water planning and management agencies.	California Water Plan
Climate Change Specific General Planning Studies	Policy Level/General	30-100 years	Typically large (statewide/Central Valley water systems)	Specifically designed to explore, estimate, and disclose climate change impacts; broad ability to explore multiple future projections. High level and broad analysis, usually not directly connected to specific decision-making. Designed to inform the legislature, public, or local/regional water planning and management agencies.	2006 and 2009 State Water Project and Central Valley Project Climate Change Impact Reports
Specific Operations Reports	Very specific to operations	20-40 years	Systemwide (typically SWP)	Specifically designed to estimate and disclose performance of SWP and project future reliability. Ability to explore multiple climate future projections has historically been limited. Often used by local and regional water users for their decision-making.	State Water Project Delivery Reliability Reports
Operations Investigation Reports	Investigative	20-80 years	Systemwide (typically SWP)	Specifically designed to test future vulnerabilities and potential strategies to improve future reliability. Ability to explore multiple future climate projections may vary. Used by DWR, legislature, and Governor's Office, to evaluate efficacy of various potential approaches to water management challenges.	System Reoperation Reports
Specific Project Analysis	Highly detailed	20-60 years	Highly localized to very large	Directly related to project level decision-making. Ability to explore multiple future climate projections is very limited. Climate change is one of many areas of very specific analysis. Implementation level, used by DWR to explore and disclose potential impacts and benefits of specific proposed projects.	Bay Delta Conservation Plan CEQA/NEPA Environmental Impact Analysis

Notes:

CEQA = California Environmental Quality Act, DWR = California Department of Water Resources, NEPA = National Environmental Policy Act, SWP = State Water Project

Table 1-3 Water Management Modeling Tools and Climate Drivers

Water Management Issue	Model Type (examples)	Key GCM Output Data Needed to Drive Existing Models
Analyses of Primary Importance		
Surface Water Supply Reliability		
Streamflow	Rainfall-runoff (VIC, SAC_SMA, HEC-HMS)	Downscaled T, P, RH
Surface Water Deliveries	Operations and Planning (CALSIM-II, WEAP)	Downscaled T, P, RH via R-R
Reservoir storage	Operations and Planning (CALSIM-II, WEAP)	Downscaled T, P, RH via R-R
Runoff Timing	Rainfall-runoff (VIC, SAC-SMA, HEC-HMS)	Downscaled T, P, RH
Delta Salinity	ANN+Operations (CALSIM-II, DSM2)	Downscaled T, P, RH via R-R, SLR
Environmental Flows		
Streamflow	Rainfall-runoff (VIC, SAC_SMA, HEC-HMS)	Downscaled T, P, RH
Reservoir temperature	Rainfall-runoff+ Reservoir Simulation	Downscaled T, P, RH
Reservoir storage	Operations and Planning (CALSIM-II, WEAP)	Downscaled T, P, RH via R-R
Air temp	GCM	Downscaled T
Groundwater Conditions	Groundwater model (MODFlOW)	Downscaled T, P, RH
Hydropower		
Streamflow	Rainfall-runoff (VIC, SAC_SMA, HEC-HMS)	Downscaled T, P, RH
Reservoir storage	Operations and Planning (CALSIM-II, WEAP)	Downscaled T, P, RH via R-R
Water Demand (Ag and Urban)	Land Use Model, ET Calcs	Downscaled T, P, RH
Flood Risk		
Precip intensity	GCM	Downscaled T, P, RH
Precip duration	GCM	Downscaled T, P, RH
Maximum flows (3, 7, 10 day)	Rainfall-runoff (VIC, SAC_SMA, HEC-HMS)	Downscaled T, P, RH
Analyses of Secondary Importance		
Wildfire	Wildfire model	Downscaled T, P, RH, W_s, etc.
Agricultural Productivity	Ag Productivity	Downscaled T_{ave}, T_{max}, T_{min}, P, RH, etc.
Others		
Ecosystem Services	Multiple	Varies

Notes:

CALSIM-II = California Water Resources Simulation model, ET = Evapotranspiration, GCM = Global Climate Model, HEC-HMS = Hydrologic Engineering Center- Hydrologic Modeling Center model, MODFLOW = USGS 3-D groundwater model, P = Precipitation, RH = Relative Humidity, R-R = rainfall runoff model, SAC-SMA = Sacramento Soil Moisture Accounting model, T = Temperature, VIC = Variable Infiltration Capacity, WEAP = Water Evaluation and Planning model, W_s = wind speed

Linkages to Local and Regional Water Planning and Management

DWR's mission includes working with and supporting water management activities by local and regional entities throughout the state. In addition to studies and analysis performed by DWR, there are a number of other planning activities performed by local or regional resource managers but which DWR supports or influences. Table 1-4 shows the major planning activities that DWR supports, and Box 1-2 provides a list of additional local planning processes that may incorporate data or analysis provided by DWR. In these planning activities, climate change information provided by DWR may be used to inform analysis or decision-making at the local level. Beyond the information DWR provides, data and methodological approaches used by DWR have often been adopted by local agencies.

This report is focused on providing perspectives and guidance for DWR's internal activities and on analysis it performs that may be used by local agencies in their planning activities. These perspectives and the guidance have been specifically developed based on DWR's capacity, existing resources, models, and tools. This advice may not be applicable to other agencies that have greater or lesser capacities or resources or that use different models or tools for their planning.

DWR and the CCTAG recognize that the need for climate change analysis for regional and local water planning and management goes beyond State water and flood management systems. The capacity to perform climate change analysis varies greatly among local agencies and water planning regions. While some agencies have been able to engage consultants and academic research groups to assist with developing, understanding, and using climate change information, many agencies and organizations lack the technical and financial capacity to incorporate climate change risks into their planning. In particular, small water systems in rural regions and rural and urban economically disadvantaged communities face challenges in performing climate change analyses.

Previous efforts by DWR and others, such as the *Climate Change Handbook for Regional Water Planning* (California Department of Water Resources et al. 2011) have provided much-needed guidance on these subjects. Nonetheless, continuous scientific evolution and ever-expanding and improving approaches, tools, and resources necessitate periodic updates to the state of the practice. To continue the process of addressing these needs, the CCTAG has provided recommendations on future activities that DWR could undertake to update and improve the tools, resources, and guidance on climate change analysis that it provides to local and regional agencies (see Chapter 5).

Table 1-4 Programs Supported By DWR

Program	Periodicity	Capability/ Applicability of Conducting General Climate Change Impacts Analysis	Extreme Conditions Analysis Conducted to Date	Capability/ Applicability of Conducting Extreme Conditions Analysis	Agency
Central Valley Flood Protection Planning	5 years	Limited applicability, flood protection vulnerabilities and impacts are predominantly driven by extreme events.	Pilot study of threshold analysis (flood)	In development	DWR staff under auspices of CVFPB
Urban Water Management Planning	5 years	Limited — this type of analysis is not explicitly required of UWMP.	Worst 3-year drought on record	Varies by local water district	Local water districts
Agricultural Water Management Planning	5 years	Required to “include an analysis, based upon available information, of the effect of climate change on future water supplies” (Water Code Section10826 [c]). Interpretation of this requirement left to DWR and AWMP groups. Capacity to conduct analysis varies among AWMPs.	No requirement	Varies by local water district	Local agricultural water suppliers
Integrated Regional Water Management Planning	Varies — depends on funding cycles	Required to evaluate "the adaptability to climate change of water management systems in the region." Interpretation of this requirement left to DWR and RWMGs. Capacity to conduct analysis varies among RWMGs.	No requirement	Varies by RWMG	RWMGs
Regional Flood Management Planning	No requirement	Limited — this type of analysis is not a focus of the grant funding.	Rely on existing studies, no new analysis	Limited — this type of analysis is not a focus of the grant funding.	Regional Flood Management Groups
Groundwater Management Planning	No requirement	Limited — this type of analysis is not required in legislation and not a focus of the grant funding.	No requirement	Limited — this type of analysis is not a focus of the grant funding.	Local Groundwater Management Groups

Notes:

AWMP = agricultural water management plan, CVFPB = Central Valley Flood Protection Board, DWR = California Department of Water Resources, RWMG = regional water management group, UWMP = urban water management plan

Box 1-2 Additional Local Planning Processes that May Be Informed by DWR Data or Analysis

DWR data and analysis are often used in various types of local plans and assessments, such as those listed below, and can play an important role in local and regional planning.

- Regional and local climate adaptation plans.
- Habitat conservation plans.
- Local hazard mitigation plans.
- Local stormwater and flood management plans.
- County and municipal general plans.
- Watershed assessments.

Linkages to Other Related Activities Being Performed by State Agencies

California produces periodic scientific assessments on the potential impacts of climate change in California and reports potential adaptation responses as required by Executive Orders S-03-05 and B-30-15. These assessments influence legislation and inform policy-makers. Previous California climate change assessments were completed in 2006, 2009, and 2012 (http://www.climatechange.ca.gov/climate_action_team/reports/climate_assessments.html). The Fourth California Climate Change Assessment is due to the Governor and Legislature in 2018 and will cover multiple parts of the economy, including public health, energy, agriculture, ecosystems, and water resources. The perspectives and guidance in this report are focused on water studies. Moreover, in practice, many if not all of the water specific considerations would also have important ramifications for other sectors. Thus, the specific model recommendations and other perspectives would also apply to other types of studies, such as impacts and adaptation options for the energy sector. In addition, a consistent set of climate change projections is desirable across State-level studies for several reasons, including the ability to compare results for different sectors and coordinate multi-sectoral studies. For these reasons, the recommendations and perspectives in this report may be useful and informative for the Fourth California Climate Change Assessment steering committee.

In addition to previous California Climate Change Assessments and the upcoming Fourth Assessment, the State has issued two important climate change guidance documents whose use and implementation could be influenced by the perspectives and guidance in this report.

First, In July 2012, the California Emergency Management Agency and the California Natural Resources Agency issued the *California Climate Adaptation Planning Guide* (APG) (California Office of Emergency Management et al. 2012). The APG presents the basis for climate change adaptation planning and introduces a step-by-step process for local and regional climate vulnerability assessment and adaptation strategy development. The information in this CCTAG report can be used to help State, regional, and local agencies implement APG recommendations, as well as to inform future updates to the APG.

Second, in July 2014, the Natural Resources Agency issued the plan, *Safeguarding California: Reducing Climate Risk* (California Natural Resources Agency 2014), which provides policy guidance for State decision-makers and is part of continuing efforts to reduce climate impacts and prepare for climate risks. The plan, which updates the 2009 California Climate Adaptation Strategy, highlights climate risks in nine sectors in California, discusses progress to date, and provides sector-specific recommendations. The information in this CCTAG report can be used to help State, regional, and local agencies implement recommendations in the *Safeguarding California Plan*, as well as to inform future updates to the plan.

Chapter 2. Global Climate Model Selection

The following key points are called out in the body of the chapter and are given supporting explanation.

Key Point 2.1

Using an ensemble or group of several simulations from different global climate models (GCMs) for planning studies is the current best practice to consider the range and uncertainty of future climate projections.

Key Point 2.2

A 3-step model screening process was developed to identify a subset of GCMs to use for California water resources investigations. This procedure was based on evaluations of GCM historical performance at the global scale, across the Southwestern United States, and for specific needs of California water resources planning.

Key Point 2.3

This 3-step evaluation process identified 10 GCMs for use in California water resources planning (Table 2-4). However, this list of models should be reviewed regularly and revised when advances in climate science, updates to GCMs, and/or changes in user needs might warrant revisions.

Additional findings from this GCM review process are as follows:

- The precipitation and temperature variability and changes presented by the 10 GCMs are a reasonable sample of the broad distribution of variability and change from the original set of 31 GCMs that were considered.
- Future projections from the selected set of 10 GCMs were evaluated for two future greenhouse gas scenarios (Representative Concentration Pathway (RCP) 4.5 and RCP 8.5 simulations), and the degree of warming and the tendency toward drier or wetter than climatological averages were calculated for the late 21st century. Also, the driest and wettest multi-year spell characteristics, driest and wettest year, and maximum 3-day wet spell characteristics during the 21st century were determined for each GCM simulation. Detailed results from this analysis are presented in Appendix B of this report.
- The screening process focused on data directly from the GCMs instead of examining data that had been downscaled to the regional level, so that the analysis would not be influenced by the choice of downscaling method.
- Although the criteria for the screening process did not consider whether each GCM's results could be used for regional dynamical modeling (a means of scaling the global results down to the regional level), 8 of the 10 GCMs selected provide the output required to drive regional dynamical downscaling models (Table 2-4). For more information on dynamical downscaling, see Chapter 4.

Introduction

Global Climate Models

Global climate models (GCMs) provide simulations used to investigate possible future climate variability and changes (e.g., Schmidt 2009; Barsugli et al 2009; Taylor et al. 2012; Intergovernmental Panel on Climate Change 2013). Observations of past climate from instrumental records and proxy indicators are also valuable guides to the future, but simulations from GCMs are the primary means of looking forward in a quantitative fashion. GCMs are numerical representations of the coupled atmosphere-ocean-land system. They are "driven" by known or assumed climate forcings, including fluctuations in solar energy, volcanic activity, changing greenhouse gas (emissions) concentrations, aerosols, and land use changes. GCMs are run prospectively over the 21st century to explore scenarios of how the climate may evolve in the future. These future climate projections represent ways the climate could change in the future, but they are not predictions or forecasts of future conditions. GCMs also are run over the past several 10year periods to provide a model version of the historical record, from which changes during the projected period can be compared and referenced. Additionally, the GCM historical runs are crucially important because they provide a basis of comparison with observed climate at global and regional scales.

GCM simulations are not perfect forecasts (e.g., Knutti 2008; Schmidt 2009; Schmidt and Sherwood 2014). Climate projections are affected by different forms of uncertainty (Hawkins and Sutton 2011), including uncertainties in climate forcing, which is caused by substances such as aerosols and greenhouse gases (Intergovernmental Panel on Climate Change 2013); uncertainties in the model representation of the real climate system (Schmidt and Tebaldi 2008); and the uncertainty that results in natural variability (Deser et al. 2012). Regional modeling and downscaling introduce additional uncertainty, owing to model uncertainties and observational errors and uncertainties (Pierce et al. 2013).

The recent generation of climate models provided by an international collective of modeling centers to the *Fifth Assessment Report of the Intergovernmental Panel on Climate Change* (IPCC AR5) and the *Coupled Model Intercomparison Project Phase 5* (CMIP5) has more models, higher resolution, and more complexity than the previous generation of GCMs, known as AR4 (Fourth Assessment) or CMIP3 (Coupled Model Intercomparison Project Phase 3) GCMs. Many of the CMIP5 models contain more interactive components, where for example atmospheric chemistry and aerosols are now interactive. Some CMIP5 models are Earth System Models (ESMs), containing a representation of biogeochemical cycles. Simulations from the CMIP5 models have been shown to be somewhat improved in their representation of observed climate over those from the previous CMIP3 GCMs (e.g., Intergovernmental Panel on Climate Change 2013; WG1 2013; Polade et al. 2013).

By the time the Climate Change Technical Advisory Group's (CCTAG's) exploration of climate model simulations began in 2013, simulations from 31 GCMs had been contributed to the CMIP5 archive. The 31 GCMs all had daily simulations of historical and 21st-century projected climate for the RCP 4.5 and RCP 8.5 scenarios (see RCP description below). Presently, the number of GCM simulations in the CMIP5 archive has increased considerably, but time and the relatively short tenure of the CCTAG did not permit revisiting the additional available GCMs.

RCP Climate Scenarios

To investigate possible future climate change, climate modelers employ a standard set of assumed scenarios of future global greenhouse gas emissions, land use, population growth, technology, and other factors. A set of future scenarios, expressed as the amount, by the year 2100, of Earth's radiative imbalance in Watts per square meter of Earth's surface. The radiative imbalance, the incoming solar energy minus outgoing energy radiated to space, is standardized as the imbalance in the year 2100 relative to a calculated pre-industrial value. The time-varying scenarios, which are used to prescribe forcing inputs to the climate models, called Representative Concentration Pathways or RCPs, were introduced in the Fifth IPCC Assessment (Taylor et al. 2012; Intergovernmental Panel on Climate Change 2013). In addition to describing emissions, the RCPs also include land-use change scenarios. There are four standard RCPs: RCP2.6, RCP4.5, RCP6.5, and RCP8.5, which represent increases in end of century radiative forcings of +2.6, +4.5, +6.5, and +8.5 Watts per square meter (W/m^2), respectively. The RCP 2.6 scenario is a relatively low greenhouse-gas emission scenario, while RCP 4.5, RCP 6.5, and RCP 8.5 appear as reasonable choices to represent low and high emissions scenarios, given current rates of global fossil fuel consumption and economic development. At the time when the CCTAG investigation began, the RCP4.5 and RCP8.5 scenario simulations were available for most GCMs, while the RCP 2.6 and RCP 6.5 were not as commonly available. Thus, for this report, the investigation is confined to RCP4.5 and RCP8.5.

Three-Step Process for Identifying GCMs for California Water Resources Planning

Key Point 2.1: Using an ensemble or group of several simulations from different global climate models (GCMs) for planning studies is the current best practice (Knutti 2008; Barsugli et al. 2009; Brekke et al. 2008; Pierce et al. 2009; McSweeney et al. 2012) to consider the range and uncertainty of future climate projections.

Key Point 2.2: A 3-step model screening process was developed to identify a subset of GCMs to use for California water resources investigations. This procedure was based on evaluations of GCM historical performance at the global scale, across the Southwestern United States, and for specific needs of California water resources planning.

The large set of CMIP5 model simulations, which has grown in number from the set of 31 GCMs that were available when the CCTAG process began, provides a valuable resource in probing possible future climate change. It provides a state-of-the-art view of climate change from a probabilistic approach. On the other hand, this large collection of model simulations is a challenge to many users and decision-makers because of the large amount of data and number of simulations to process, analyze, and evaluate. Previous efforts that evaluated GCM performance for Northern California (Brekke et al. 2008) found that an ensemble (group of models) in general performed better than the individual models when a broad range of historical climate metrics were considered. Different GCMs performed best for different metrics, and when multiple metrics were considered, no individual model emerged as the "best" model for California. Recognizing the need for multiple GCMs, as well as the requirement for a smaller set of simulations, this model evaluation effort aimed to identify a smaller set of GCMs by removing or "culling" the models that did not perform as well for a set of different evaluation metrics. It is emphasized that this is not a comprehensive analysis of GCM performance, and a given GCM should not be labeled "good" or "bad" based on this analysis. The goal of this analysis was to reduce the total number of GCMs by choosing those that performed better for criteria specifically selected for California water resources planning purposes.

Selecting a smaller subset of models requires a set of GCMs that perform reasonably well in simulating historically observed climate. Evidence has been shown that reducing the number of GCMs too severely will likely under-sample global and regional climate futures; a subset of 10 or more GCMs is needed to describe the rather wide distribution of possible climate variations and changes that could occur in future 10-year periods (e.g. Pierce et al 2009; McSweeney et al. 2012).

To identify a subset of the “better” GCMs for developing assessments and plans for California water resource issues, previous studies were followed in adopting the “direct approach” of model evaluation (Intergovernmental Panel on Climate Change 2013 [Chapter 9]), which selects GCMs on the basis of a comparison between model output and historical observations. Although many water resources planning applications used downscaled climate projections, this analysis focuses on the output from the GCMs directly to distinguish evaluation of GCM performance from artifacts of the choice of downscaling method.

A 3-step evaluation approach was used to identify a tractable set of GCMs for California water resources planning (see Figure 2-1). The first two steps of the process evaluate GCM simulations of historical climate at the global and Western United States scales. After work by Gleckler (2008), the Intergovernmental Panel on Climate Change (IPCC) (2013), and Rupp et al. (2013), an evaluation was conducted based on a collection of scalar metrics to gauge GCM historical simulations against various observational data. Global metrics (Gleckler 2008) include the root-mean-square error (RMSE) of the seasonal cycle of selected global atmospheric fields, including radiative measures, winds, precipitation, and temperature. Regional metrics (Rupp et al. 2013) included correlation and variance of mean seasonal spatial patterns, amplitude of seasonal cycle, diurnal temperature range, annual- to decadal-scale variance, long-term persistence, and Western United States regional precipitation teleconnections to El Niño Southern Oscillation (ENSO). For the third step of the evaluation process, a set of metrics was developed to test the GCMs’ skill in simulating California climate and hydrological variability. The metrics for all three steps of the evaluation process are summarized in Table 2-1.

In selecting subsets or weighting climate model simulations, caution is warranted. First, it has been shown that no strong relationship exists between model performance and the model’s climate sensitivity (Intergovernmental Panel on Climate Change 2007). Second, there is no strong evidence indicating that the degree of model performance has a strong influence on the credibility of projections (e.g., Pierce et al. 2009). Nonetheless, there is little to gauge the suitability of a climate model other than its performance in simulating observed climate. Accordingly, this effort evaluated GCM simulations of historical climate relative to selected metrics. The models were not evaluated on any characteristics of their future projections. Not unlike mutual funds in economics, though past performance is no guarantee of future performance, the model’s representation of historical climate provides a logical way to select models for regional application.

Figure 2-1 Three-Step Process for Selecting Global Climate Models to Use for California Water Resources

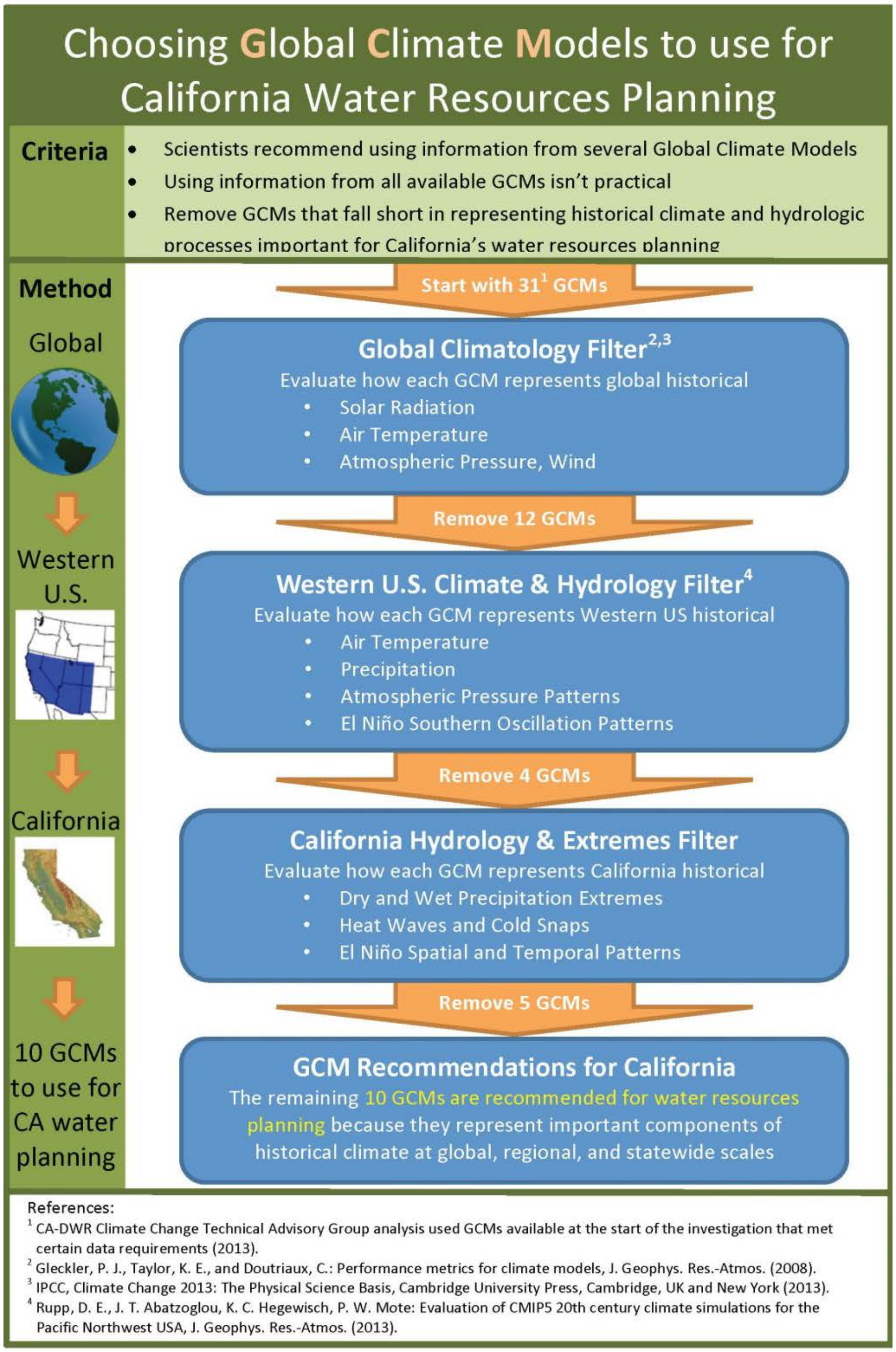


Table 2-1 Evaluation Metrics for Selecting Global Climate Models to Use for California Water Resources

Metric	Description
Global Metrics (Gleckler et al. 2008)	
LW CRE, SW CRE	Longwave (LW) or Shortwave (SW) Cloud Radiative Effects
RSUT, RLUT	Top of the Atmosphere Reflected Shortwave & Longwave Radiation
PR	Total Precipitation
TAS	Surface Air Temperature
ZG (500hPa)	Geopotential Height
VA (200hPa), VA (850hPa) UA (200hPa), UA (850hPa)	Meridional (VA, North-South) and Zonal (UA, West-East) wind speeds at two different levels in the atmosphere 200hPa and 850hPa
TA (200hPa), TA (850hPa)	Temperature at two different levels in the atmosphere 200hPa & 850hPa
Western United States Metrics (Rupp et al. 2013)	
Mean-T and Mean-P	Mean Annual Temperature (T) and Precipitation (P), 1960-1999
DTR-MMM	Mean diurnal temperature range, 1950-1999
SeasonAmp-T SeasonAmp-P	Mean amplitude of seasonal cycle, as the difference between warmest and coldest month (T) or between wettest and driest month (P), 1960-1999 Monthly precipitation calculated as percentage of mean annual total
SpaceCor-MMM[a]-T SpaceCor-MMM-P	Correlation of simulated with observed the mean spatial pattern of temperature and precipitation, 1960–1999
SpaceSD-MMM-T SpaceSD-MMM[*]-P	Standard deviation of the mean spatial pattern of temperature and precipitation, 1960-1999
TimeVar.1-T to TimeVar.8-T	Variance of temperature calculated at frequencies (time periods of aggregation) ranging for N=1 and 8 years, 1901–1999
TimeCV.1-P to TimeCV.8-P	Coefficient of variation (CV) of precipitation calculated at frequencies (time periods of aggregation) ranging for N=1 & 8 water years[b], 1902–1999
Trend-T and Trend-P	Linear trend of annual temperature and precipitation, 1901–1999
ENSO-T and ENSO-P	Correlation of winter temperature and precipitation with Niño 3.4 index, 1901-1999
Hurst-T and Hurst-P	Hurst exponent using monthly difference anomalies (T) or fractional anomalies (P), 1901-1999
California Water Resources Metrics	
Std dev # dry years/10-year period	Standard deviation of 10-year totals of the number of dry years
3-day maximum precipitation	Maximum 3-day total precipitation, as a ratio of average water year[b] precipitation 1961-1990 (%)
El Niño Pattern Correlation	Spatial structure of correlation of precipitation to the Niño 3.4 ENSO index derived from a GCM, gauged by pattern correlation to that from historical observations
El Niño Temporal Variation	Niño 3.4, temporal variation, a measure of the El Niño Southern Oscillation
Miscellaneous	
Model Family	No more than two models from the same model family were included in the selected set of models to represent model diversity.

Notes:

[a]MMM is the season designation: DJF (Dec Jan Feb), MAM (Mar Apr May), JJA (June July Aug), and SON (Sep Oct Nov).

[b]Water years are October to September instead of the calendar year from January to December.

For GCM background information and affiliated research institutions, see CMIP5 Coupled Model Intercomparison Project at http://cmip-pcmdi.llnl.gov/cmip5/availability.html.

Each step of the GCM evaluation process is described in more detail below. Table 2-2 lists the GCMs that were evaluated and indicates at which step of the evaluation that model was retained or removed from consideration. The 10 GCMs remaining after the global, Western United States, and California assessment steps are the models selected for use in California water resources planning.

Table 2-2 Global Climate Model Evaluation for Use for California Water Resources

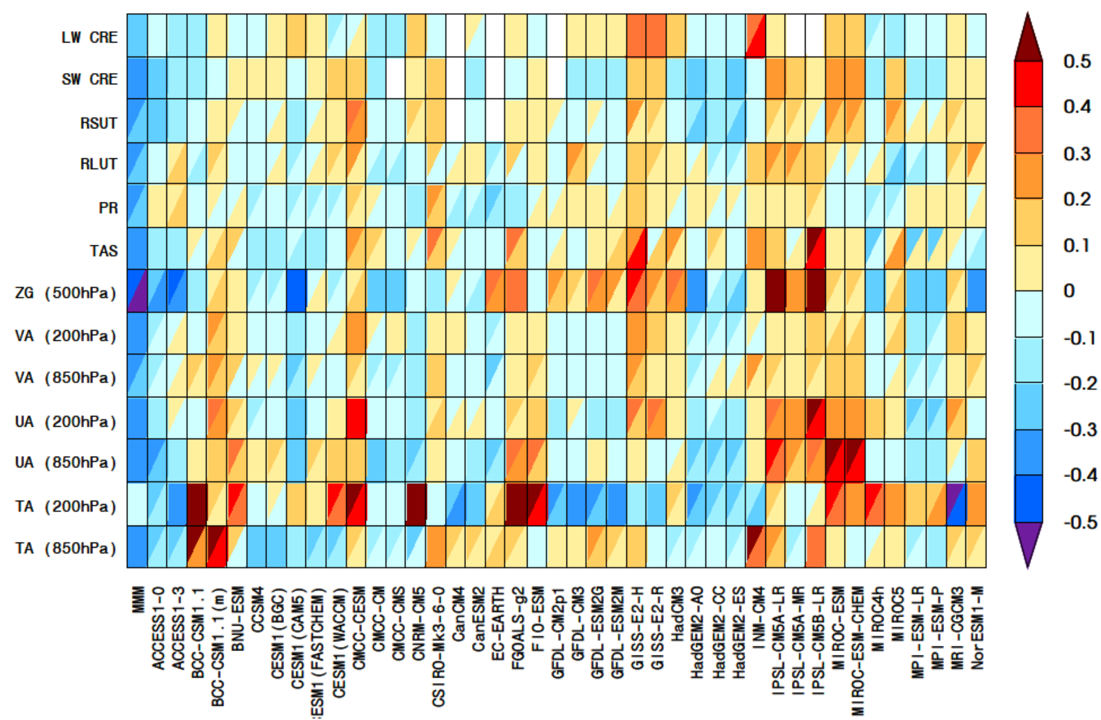
Global Climate Model	Evaluation step where model was removed from consideration. Remaining models are selected for use for California water resources.		
	Global	Regional	California
ACCESS-1.0			
CanESM2			
CCSM4			
CESM1-BGC			
CMCC-CMS			
CNRM-CM5			
GFDL-CM3			
HadGEM2-CC			
HadGEM2-ES			
MIROC5			
BCC-CSM1-1			
CESM1-CAM5			
CMCC-CM			
GFDL-ESM2M			
MPI-ESM-LR			
BNU-ESM			
GFDL-ESM2G			
MRI-CGCM3			
NORESM1-M			
ACCESS-1.3			
BCC-CSM1-1-M			
CSIRO-MK3-6-0			
EC-EARTH			
FGOALS-G2			
INMCM4			
IPSL-CM5A-LR			
IPSL-CM5A-MR			
IPSL-CM5B-LR			
MIROC-ESM			
MIROC-ESM-CHEM			
MPI-ESM-MR			

Notes: Models that were eliminated by the global, or regional, or California screening are shaded red. The remaining models are shaded green and were selected for California water resources planning. Note that this is not a comprehensive evaluation of global climate model (GCM) performance. The evaluation was targeted at reducing the number of GCMs to use in California water resources planning. For GCM background information and affiliated research institutions, see CMIP5 Coupled Model Intercomparison Project at http://cmip-pcmdi.llnl.gov/cmip5/availability.html.

Evaluating GCMs Using Global Metrics

A set of 31 CMIP5 GCMs (Table 2-1) was evaluated using a set of global measures. Those global measures represent longwave and shortwave radiation, winds, precipitation, and temperature. Results are shown in Figure 2-2 (from Intergovernmental Panel on Climate Change 2013); an analysis patterned after the Gleckler, et al. (2008) “Performance Metrics for Climate Models.” This analysis assessed the performance of each GCM in simulating each of the global measures, judged against observed estimates of those global measures, using a RMSE approach. Consulting the IPCC 2013 screen (Figure 2-2), 19 GCMs were accepted (Table 2-2). The models that were excluded were removed because of poor skill in the model historical period in replicating parts of the global scale measures. During this stage of the screening process, consideration of model “genetics” also came into play (see below), wherein the Hadley Center HadGEM2-AO GCM was excluded and the GFDL-CM3 GCM was included.

Figure 2-2 Analysis of GCM Representation of Historical Climate Using Global Scale Metrics



Source: Reproduction of Figure 9.7 from Intergovernmental Panel on Climate Change 2013: *Climate Change 2013: The Physical Science Basis*. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change.

Notes:

Relative error measures of CMIP5 model performance, based on the global seasonal-cycle climatology (1980-2005) computed from the historical experiments. Rows and columns represent individual variables and models, respectively. The error measure is a space-time root-mean-square error (RSME), which, treating each variable separately, is portrayed as a relative error by normalizing the result by the median error of all model results (Gleckler et al. 2008). For example, a value of 0.20 indicates that a model’s RMSE is 20% larger than the median CMIP5 error for that variable, whereas a value of -0.20 means the error is 20% smaller than the median error. No color (white) indicates that model results are currently unavailable. A diagonal split of a grid square shows the relative error with respect to two re-analysis data sets: the Atmospheric Infrared Sounder (AIRS) experiment (upper-left triangle) and ERA-40 (lower-right triangle). The relative errors are calculated independently for the default and the alternate data sets. All reference data used in the diagram are summarized in Table 9.3 of the Working Group I report (Intergovernmental Panel on Climate Change 2013). For GCM background information and affiliated research institutions, see CMIP5 Coupled Model Intercomparison Project at http://cmip-pcmdi.llnl.gov/cmip5/availability.html.

Evaluating GCMs Using Regional Metrics for the Southwest United States

Following the screening using global climate metrics, a second tier of screening to identify GCMs that perform well in replicating regional climate structure was conducted. The regional screening is a procedure developed by Dr. David Rupp of Oregon State University and colleagues, as presented for the Pacific Northwest region in “Evaluation of CMIP5 20th Century Climate Simulations for the Pacific Northwest USA” (Rupp et al. 2013). CCTAG’s regional assessment used information from this screening procedure that had been applied to the Southwestern United States for nearly all of the CMIP5 GCMs evaluated (Rupp pers. comm. Sept. 20, 2013). As a result (Figure 2-3), four additional GCMs were eliminated from the 20 that had survived the global culling procedure (see Table 2-2). The GCMs removed from consideration by the regional screen were not included because of relatively poor skill in aspects of their daily and seasonal regional temperature structure, and in the level of anomalous variability of precipitation, along with other measures.

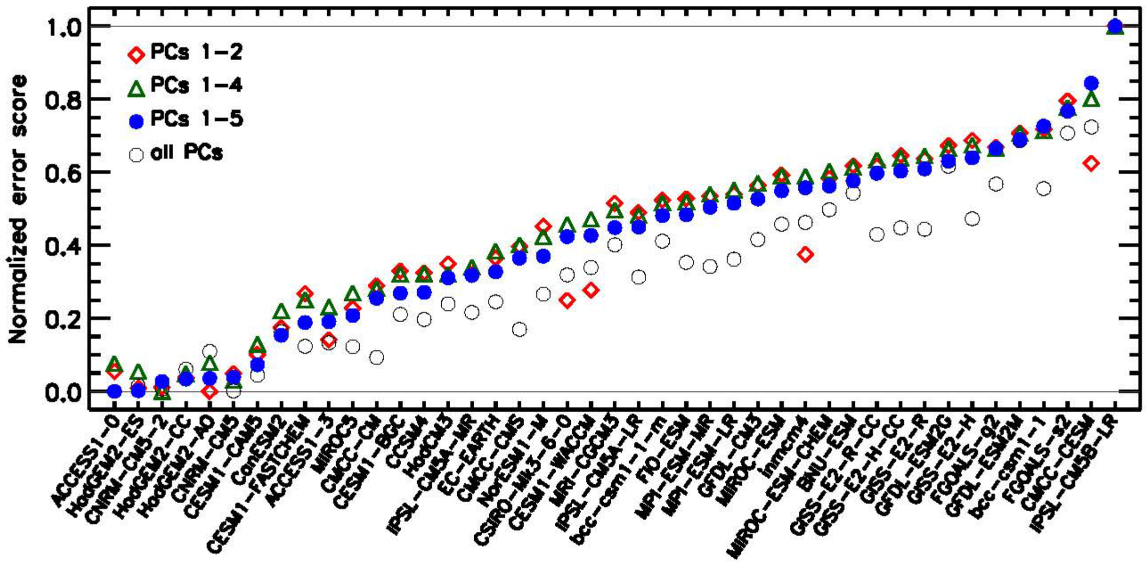
Evaluating GCMs Using California Water Management Metrics

The third tier of screening was conducted for measures that were designed to evaluate GCM performance in simulating aspects of climate germane to California climate and water resources. These metrics included the GCM’s ENSO temporal variation and the correlation of the ENSO precipitation teleconnection pattern (the relationship between warm sea-surface temperatures in the east-central Pacific and precipitation in the Sacramento region) to that from historical observations. They also included two measures of variability of standardized central California precipitation, including magnitude of variability of the number of dry years in a 10-year period. These metrics were devised to evaluate how the GCMs simulate processes that have important effects on California water management. DWR worked with the CCTAG to review the range of modeling and analytical work that DWR does for its planning and management activities. Special attention was given to the type of climatological information used to drive water resource models and specific types of conditions and variability that affect water resources management (see Table 1-3). The California specific metrics are described below and evaluation results are presented in Table 2-3.

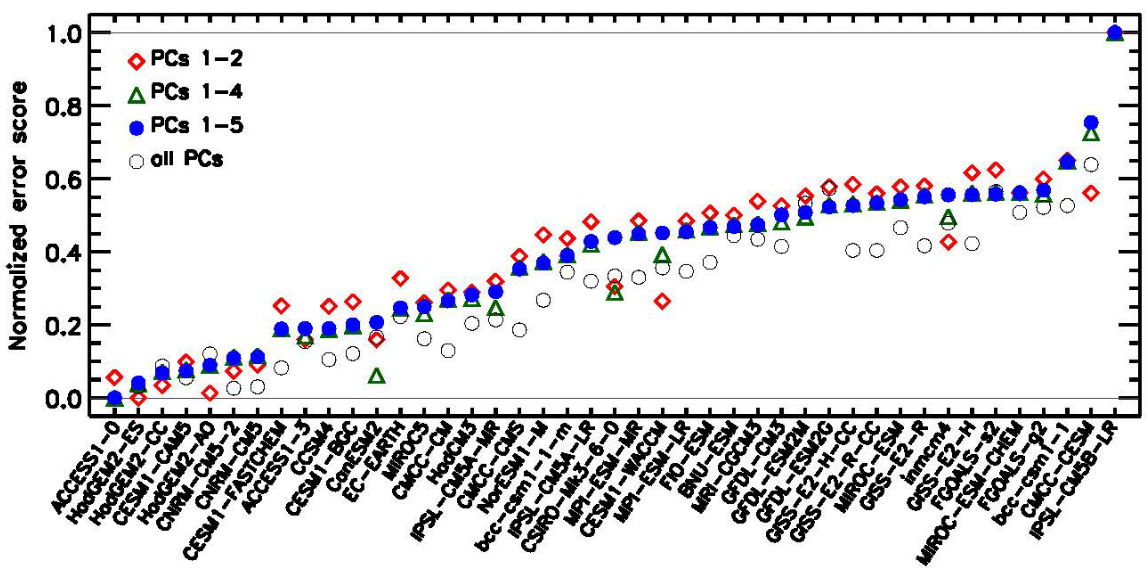
- **Standard deviation of the number of dry years per 10-year period:** a measure of how a model simulates drought periods. Sliding 10-year periods from water year (October to September) 1851 to 2005 were evaluated.
- **Maximum 3-day total precipitation:** an indication of whether a model simulates strong precipitation events, such as atmospheric river storms, which are important for California’s water supply and flood management planning. Studies have shown that California receives a significant amount of its annual precipitation from a few strong storms (Ralph and Dettinger 2012). Maximum 3-day precipitation is divided by the average simulated water-year precipitation from 1961 to 1990. For example, a value of 0.25 would mean that the maximum 3-day precipitation represents 25 percent of the average historical annual precipitation.
- **El Niño-Precipitation Pattern Correlation**: the degree of similarity, from a GCM versus observations, of the pattern formed from correlations between the Niño 3.4 sea surface temperature (a commonly used index of ENSO variability) and precipitation at grid points within the eastern North Pacific and western North America region. For the models, the ENSO-precipitation correlations were derived for model water years 1851-2005, while for observations the correlations were formed from these measures taken from 1961-1990.

Figure 2-3 Ranking of GCMs Based on Regional Performance Metrics

a) Evaluation with 22 metrics



b) Evaluation with 18 metrics from Rupp et al. 2013



Source: Rupp pers. comm. Sept. 20, 2013

Notes:

Forty-three CMIP5 global climate models (GCMs) ranked according to normalized error score from empirical orthogonal function (EOF) analysis of performance metrics. Ranking is based on the first five principal components (PCs, filled blue circles). The open symbols show the models' error scores, using the first 2, 4, and all 22 PCs. The best scoring model has a normalized error score of zero.
For GCM background information and affiliated research institutions, see CMIP5 Coupled Model Intercomparison Project at http://cmip-pcmdi.llnl.gov/cmip5/availability.html.

- **El Niño Temporal Variation:** Models that produce realistic El Niño time variations were desired for California water resources planning. The temporal variation of the Niño 3.4 sea surface temperature anomaly was examined visually from time series plots to gauge how well a model represents the temporal pattern of the ENSO. Models that had ENSO patterns that occurred too regularly, for example an El Niño every four years, were removed from consideration.

Evaluating GCM Genetics

An additional consideration when selecting a subset of 10 GCMs was model genetics. GCMs are numerical codes that solve the fundamental conservation and process equations, so to some extent they are all related (Knutti et al. 2013; Swanson 2013). Some are very closely related because they share common numerics or physical components. In "Climate Model Genealogy: Generation CMIP5 and How We Got There" (Knutti et al. 2013), "model genetics" of CMIP5 GCMs are described, providing some insight into the degree of similarity between CMIP5 GCMs. The CCTAG screening exercise tried to avoid redundancy by not selecting more than two GCMs from the same modeling group. Also, an attempt was made to increase diversity by including models that might otherwise have been eliminated by one of the screening metrics. Thus, consideration of model "genetics" led to exclusion of the Hadley Center HadGEM2-AO GCM, to avoid using more than two GCMs from the Hadley Center, and to include the GFDL-CM3 GCM, which had only modest overall skill based on the global screen but good performance in the regional and California metrics.

Table 2-3 Global Climate Model Performance for California Metrics

Global Climate Model	Standard Deviation # of dry yrs/ 10 years	3-Day Max Precip/Annual Avg Precip (%)	El Niño Pattern Correlation	El Niño Temporal Variation
ACCESS-1.0	1.11	0.24	0.52	
BCC-CSM1-1	1.59	0.12	0.20	Pattern variation was too regular
CCSM4	1.24	0.19	0.51	
CESM1-BGC	1.16	0.20	0.38	
CESM1-CAM5	1.60	0.26	-0.47	Pattern variation was too regular
CMCC-CM	0.95	0.22	0.46	
CMCC-CMS	1.04	0.19	0.58	
CNRM-CM5	1.32	0.15	0.30	
CanESM2	1.69	0.19	0.28	
GFDL-CM3	1.14	0.17	0.31	
GFDL-ESM2M	1.90	0.16	0.18	
HadGEM2-CC	1.45	0.27	0.43	
HadGEM2-ES	1.08	0.25	0.52	
MIROC5	1.54	0.17	0.44	
MPI-ESM-LR	1.02	0.18	0.10	

Notes: Global climate models (GCMs) in this subset are those that remained after global and regional screening. Those GCMs with grey shading were discarded based on one or more (orange colored) California metrics. For GCM background information and affiliated research institutions, see CMIP5 Coupled Model Intercomparison Project at http://cmip-pcmdi.llnl.gov/cmip5/availability.html.

The California evaluation revealed that some of the GCMs did not perform well in one or more of the California water management metrics, which led to the elimination of an additional five GCMs (Table 2-3). GCMs that were not accepted by the California screens were excluded because of unrealistic ENSO temporal or spatial structure, inadequate (too low) variability of multi-year dryness, or unsuitably low magnitudes of extremely heavy precipitation. Note that both the models with the greatest projected warming (CanESM2) and least projected warming (MIROC5) were among the models that were retained after this evaluation. The resultant subset was 10 GCMs selected on the basis of providing realistic historical climate simulations of global, Southwestern United States and adjacent regions, and California region water-management-relevant climate measures. The 10 CMIP5 GCMs that passed the collective screening process are:

1. ACCESS-1.0.
2. CCSM4.
3. CESM1-BGC.
4. CNRM-CM5.
5. CanESM2.
6. GFDL-CM3.
7. HadGEM2-CC.
8. HadGEM2.
9. ESMIROC5.
10. CMCC-CMS.

Some details about these 10 models are presented in Table 2-4 of the "Individual Model Wet and Dry Spell Characteristics" section later in this chapter. For GCM background information and affiliated research institutions, see CMIP5 Coupled Model Intercomparison Project at http://cmip-pcmdi.llnl.gov/cmip5/availability.html.

Key Point 2.3: This 3-step evaluation process identified 10 GCMs to use in California water resources planning. However, this list of models should be reviewed and revised when advances in climate science, updates to GCMs, and/or changes in user needs warrant possible revisions.

How Representative Are the 10 Selected GCMs of the Larger Set of 31 Models?

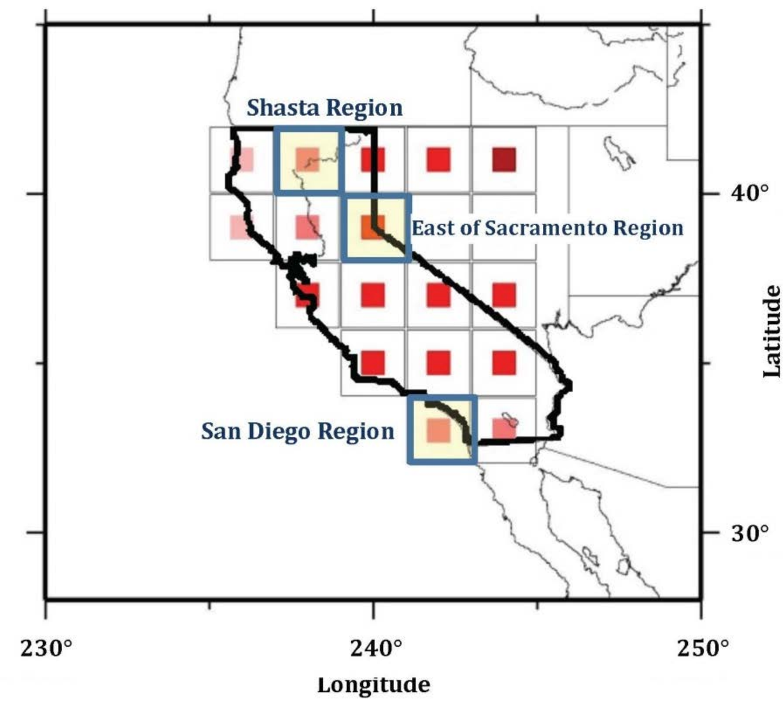
To investigate how the ensemble of 10 selected GCMs compares with the larger ensemble of 31 GCMs, the data from all of the models was interpolated to a common 2-degree-longitude by 2-degree-latitude grid. This enabled comparison of a variety of different metrics of temperature and precipitation change and interannual variability for the two ensembles. The matrix of grid cells (19 in all) over the California/Nevada region is shown in Figure 2-4. Three grid cells were selected for the comparison analysis: centered at 41N and 122W, near Shasta, California (40.6N; 122.5W); centered at 39N and 120W east of Sacramento; and centered at 33N and 118W near San Diego.

Pertinent to the selection of a subset of GCMs for California water resource assessment is how broadly the selected subset represents the overall range of temperature and precipitation changes (Tebaldi and Sanso 2009; Andrews et al. 2012) that is presented by the larger sample of CMIP5 GCMs (e.g., McSweeney et al. 2014). To make this assessment, the temperature and precipitation changes from the 10 selected GCMs (Table 2-4) were compared with the original set of 31 CMIP5 GCMs (Table 2-2). First, a set of “spaghetti plots” (Figures 2-5 and 2-6) show annual values of temperature and precipitation from the 10 selected models, plotted as time series compared with the envelope of those of the overall 31-member ensemble. Second, temperature versus precipitation changes (2070-2099 versus 1961-1990) for the 10 selected GCMs, compared with the remaining 31 GCMs, are plotted in Figure 2-7. For both sets of figures, results are shown for the lower (RCP 4.5) and higher (RCP 8.5) future emissions scenarios.

Concerning warming trends, under RCP 4.5 (Table 2-5, Figure 2-5a, Figure 2-7a), the temperature changes range from 3.5 °F to 6 °F (1.9 to 3.3 ºC) warmer than historical mean compared with an overall range of 3 °F to 6.5 °F (1.7 to 3.6 ºC) for the large ensemble of 31 GCMs. Under the RCP 8.5 scenario (Table 2-5, Figure 2-5b, Figure 2-7b), the temperature changes range from 6.5 °F to 10 °F (3.6 to 5.6 ºC) greater than historical mean compared with an overall range of 5.5 °F to 10.5 °F (3.1 to 5.8 ºC) for the large ensemble of 31 GCMs.

From the 10 selected models, the East of Sacramento Region precipitation changes 2070-2099 versus 1961-1990 represent quite well those from the large ensemble, as shown in Figures 2-6 (a and b). Under the RCP 4.5 scenario, the precipitation changes range from 88 percent to 125 percent of historical mean compared with an overall range of 85 percent to 125 percent for the large ensemble of 31. Nonetheless, the number of RCP 4.5 simulations in the 10-member subset whose precipitation becomes drier than historical mean is proportionately smaller than the fraction of GCMs becoming drier in the large ensemble of 31. The number of drying and wetting RCP 8.5 simulations in the 10-member subset seems consistent with the overall 31 member distribution. Under the RCP 8.5 scenario, the precipitation changes range from 89 percent to 130 percent of historical mean compared with an overall range of 75 percent to 130 percent for the large ensemble of 31.

Figure 2-4 Uniform 2-Degree Grid on which Data from Each of the 10 GCMs Was Interpolated



Notes:

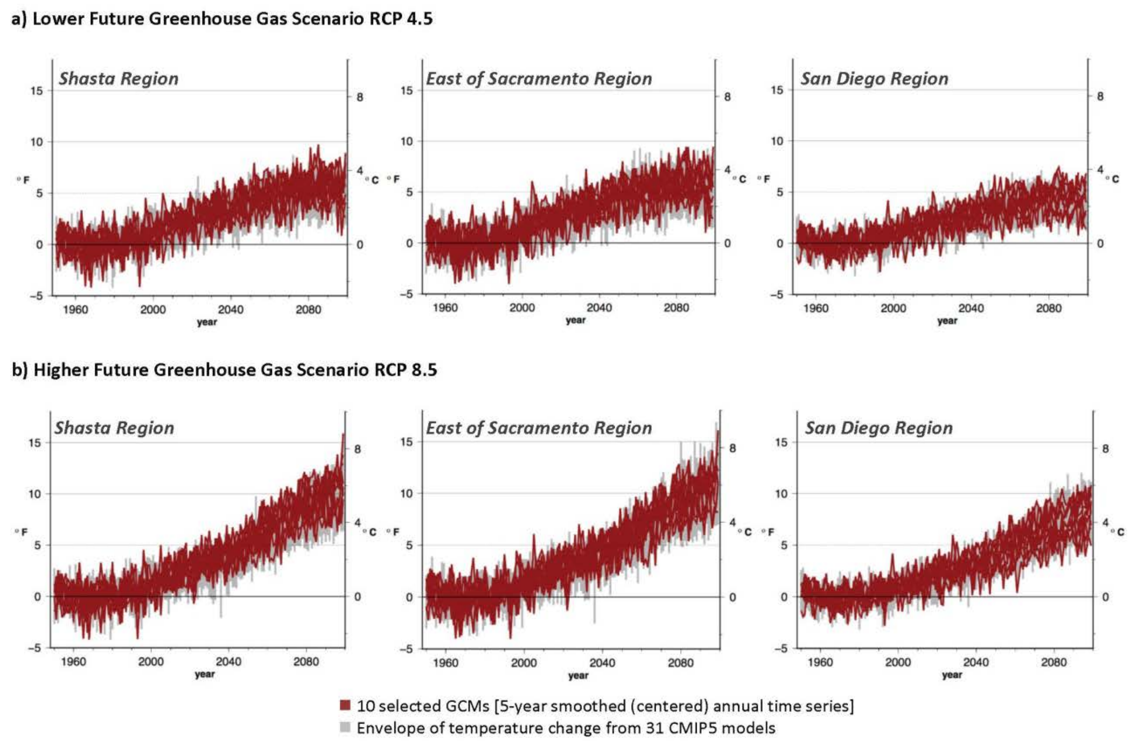
GCM = global climate model

The three highlighted locations were selected for presentation in this report.

From this rather cursory comparison of future projections of temperature and precipitation, it is concluded that the 10 selected GCMs represent a magnitude and spread of temperature and precipitation change over the 21st century similar to those of the full set of 31 CMIP5 GCMs evaluated. On the other hand, it can be seen (Figure 2-7) that some of the most extreme precipitation projections (wettest and driest) from the full set of 31 models are not represented by those 10 models.

A similar analysis was also conducted to compare the 10 selected GCMs with the six CMIP3 GCMs that were employed in the Third California Climate Change Assessment (see Appendix B1). That analysis found that these two sets of models produced similar ranges of temperature and precipitation change over the 21st century.

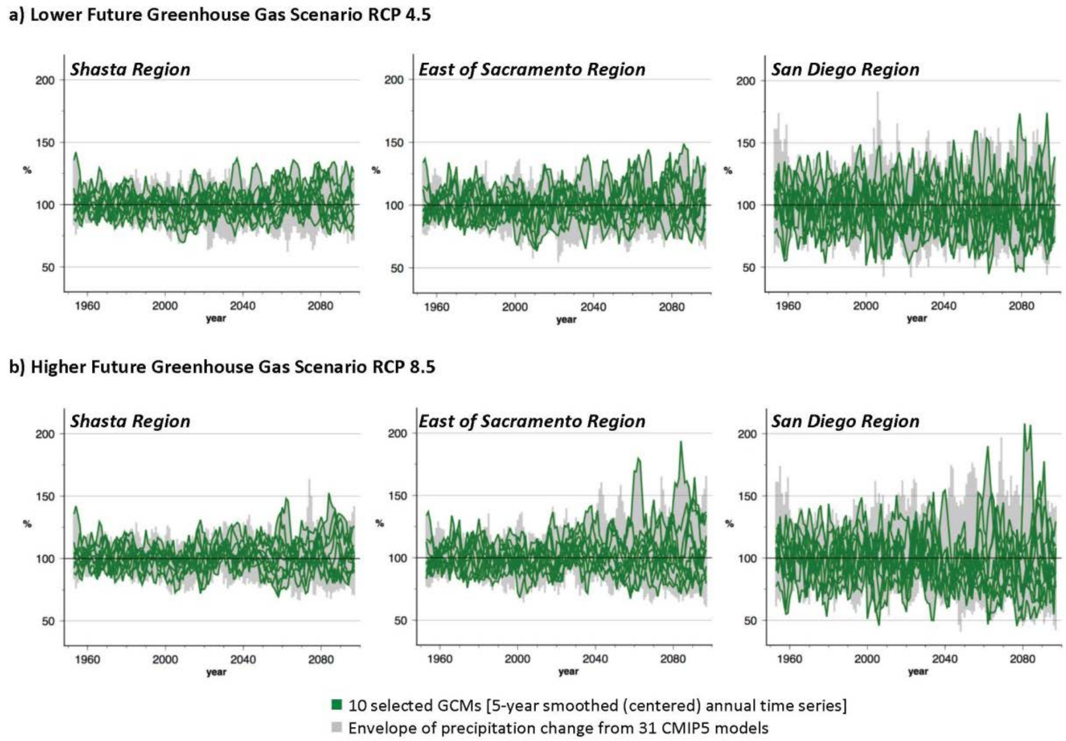
Figure 2-5 Annual Change in Temperature from GCM Simulations Relative to 1961-1990 Climatology



Notes:

GCM = global climate model

Figure 2-6 Water-Year Precipitation as the Percentage of Historical 1961-1990 Precipitation Climatology

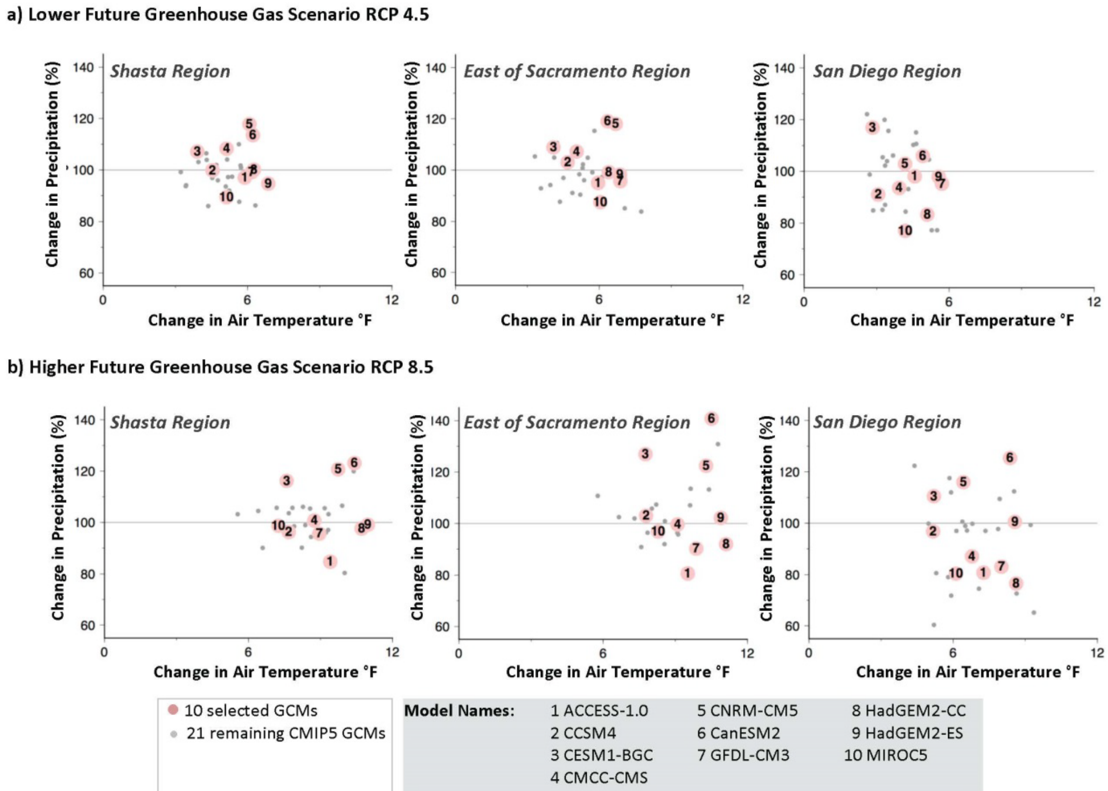


Notes**:**

GCM = global climate model

Values greater than 100 percent indicate an increase in precipitation relative to the historical average, and values less than 100 percent indicate a decrease in precipitation relative to the historical average. Water years are October-September.

Figure 2-7 Late Century Temperature and Precipitation Changes 2070-2099 versus 1961-1990 Historical Climatology



Notes:

Values greater than 100 percent indicate an increase in precipitation relative to the historical average, and values less than 100 percent indicate a decrease in precipitation relative to the historical average. For GCM background information and affiliated research institutions, see CMIP5 Coupled Model Intercomparison Project at http://cmip-pcmdi.llnl.gov/cmip5/availability.html.

Characteristics of the 10 GCMs Selected for California Water Resources Planning

In addition to temperature and precipitation projections presented in the previous section of this chapter (Figure 2-5 to Figure 2-7), the following characteristics of the 10 selected GCMs are described below or in the Appendix B.

- Model resolution and dynamical downscaling suitability.
- End of 21st century projected changes in temperature and precipitation.
- Representation of future dry and wet periods by the 10 selected GCMs (see Appendix B2).

Model Resolution and Dynamical Downscaling Suitability

For the 10 GCMs selected for use in California water resources planning, the model names and institutions that developed and/or oversaw the running of each model are listed alphabetically in Table 2-4. The resolution or spatial scale of each model's atmospheric grid (number of longitudes by number of latitudes) is also listed in Table 2-4. Larger numbers correspond to a finer or more detailed resolution for the model grid. The horizontal resolution of the 10 GCMs ranged from about 110 to 250 kilometers (km) (68 to 155 miles).

The evaluation process for selecting 10 GCMs for California did not consider whether a given GCM provided output data sufficient to serve as boundary conditions for driving regional climate model (RCM) simulations ("dynamical downscaling") (e.g., Barsugli et al. 2009; Pierce et al. 2013). However, several of the simulations within the CMIP5 GCM archive have the data for the suite of variables necessary to drive RCMs, and within the 10-member California GCM subset, eight of the GCMs did save and do provide data necessary to support RCM runs (McSweeney et al 2012), as noted in Table 2-4.

Table 2-4 Characteristics of GCMs Selected for California Water Resources Planning

Model Number	Model Name	Model Institution	Model Resolution[a]	Dynamical Downscaling[b]
1	ACCESS-1.0	CSIRO (Commonwealth Scientific and Industrial Research Organisation, Australia), and BOM (Bureau of Meteorology, Australia)	192x145 (165 km)	✓
2	CCSM4	National Center for Atmospheric Research	288x192 (110 km)	✓
3	CESM1-BGC	National Science Foundation, Department of Energy, National Center for Atmospheric Research	288x192 (110 km)	
4	CMCC-CMS	Centro Euro-Mediterraneo per I Cambiamenti Climatici	192x96 (165 km)	
5	CNRM-CM5	Centre National de Recherches Meteorologiques / Centre Europeen de Recherche et Formation Avancees en Calcul Scientifique	256x128 (123 km)	✓
6	CanESM2	Canadian Centre for Climate Modeling and Analysis	128x64 (247 km)	✓
7	GFDL-CM3	Geophysical Fluid Dynamics Laboratory	144x90 (219 km)	✓
8	HadGEM2-CC	Met Office Hadley Centre	192x145 (165 km)	✓
9	HadGEM2-ES	Met Office Hadley Centre (additional HadGEM2-ES realizations contributed by Instituto Nacional de Pesquisas Espaciais)	192x145 (165 km)	✓
10	MIROC5	Atmosphere and Ocean Research Institute (The University of Tokyo), National Institute for Environmental Studies, and Japan Agency for Marine-Earth Science and Technology	256x128 (123 km)	✓

Notes:

km = kilometers

Models are listed alphabetically.
[a] size of the model's atmospheric grid (number of longitudes by number of latitudes)
[b] A check mark indicates that the model has the necessary variables at the proper time interval for dynamical downscaling. For GCM background information and affiliated research institutions, see CMIP5 Coupled Model Intercomparison Project at http://cmip-pcmdi.llnl.gov/cmip5/availability.html.

End of 21st Century Change in Temperature and Precipitation

Table 2-5 shows changes (2070-2099 versus 1961-1990) in annual temperature and annual water-year (WY) precipitation (precipitation from October through September). To represent these changes, the grid cell east of Sacramento was selected to present in this report, but it should be noted that the changes differ depending on location (see Figures 2-5 and 2-6). In particular, the magnitude of warming increases quite markedly in the inland direction from the coast, and precipitation changes tend toward becoming drier toward Southern California and becoming wetter toward Northern California.

Table 2-5 Change in Annual Temperature (°F) and Water Year Precipitation (inches) for Region East of Sacramento from Each of the 10 Selected GCMs

Model Name	Change in Annual Temperature (°F) 2070-2099 minus 1961-1990		Change in Precipitation (in.) WY 2070-2099 minus WY 1961-1990	
	RCP 4.5	RCP 8.5	RCP 4.5	RCP 8.5
ACCESS-1.0	6.0	9.5	-1.5	-5.6
CCSM4	4.7	7.8	1.3	1.3
CESM1-BGC	4.1	7.8	3.4	10.8
CMCC-CMS	5.1	9.1	3.3	-0.2
CNRM-CM5	6.7	10.3	7.9	9.9
CanESM2	6.4	10.5	3.7	7.9
GFDL-CM3	6.8	10.1	-2.0	-4.5
HadGEM2-CC	6.4	11.1	-0.2	-1.8
HadGEM2-ES	6.9	10.9	-0.4	0.5
MIROC5	6.1	8.3	-3.8	-1.0

Notes:

GCM = global climate model, RCP = Representative Concentration Pathway, WY = water year
Red shading indicates model simulations that show relatively high warming; olive shading indicates simulations that show drying. For GCM background information and affiliated research institutions, see the CMIP5 Coupled Model Intercomparison Project at http://cmip-pcmdi.llnl.gov/cmip5/availability.html.

The models experiencing highest warming by end of 21st century under the lower future greenhouse gas scenario RCP 4.5 are the same models experiencing highest warming under the higher future greenhouse gas scenario RCP 8.5. Warming under RCP 4.5 ranges from about 4 °F to 7 °F (2.2 to 3.9 °C), while warming under RCP 8.5 ranges from 7.7 °F to about 11 °F (4.3 to 6.1 °C). To a large extent, the models that trended drier over the 21st century under RCP 4.5 were the same models that dried under RCP 8.5. Precipitation changes under RCP 4.5 ranges from about -4 inches to +8 inches (-10.2 to +20.3 cm) different from the historical climatology of annual average precipitation, and under RCP 8.5 ranges from about -5.6 inches to +10.8 inches (-14.2 to +27.4 cm) different from historical climatology.

At the annual level, the variability of temperature and precipitation appears to represent reasonably well the envelope of variability within the large ensemble (Figures 2-5 and 2-6). Notably, both warm and cool spells are present. Importantly, it appears that the magnitudes of the wettest years from the 10-member subset are generally not as wet as the wettest years in the 31-member ensemble.

The 10 CMIP5 GCM simulations provide a set of temperature increases and precipitation changes that fall into a similar range as those from six CMIP3 GCMs that were employed in the previous California Climate Change Vulnerability and Adaptation Assessment, as illustrated in Appendix B2.

Individual Model Wet and Dry Spell Characteristics

For some applications, extreme wet or dry long-term conditions may be critical for analytical purposes. To this end, the precipitation projections from the 10 selected GCMs were evaluated (Appendix B2) to identify:

- The longest consecutive dry or wet periods.
- The driest or wettest year and 10-year periods simulated.
- The highest 3-day precipitation from each model.

For these analyses, a dry year is defined as one when the precipitation is less than or equal to the 25th-percentile precipitation from 50 years of historical simulation (WY 1951 to WY 2000). Similarly, a wet year is defined as one when the precipitation is greater than or equal to the 75th-percentile precipitation of the historical simulation. Briefly summarized, these analyses indicate that:

- From the GCM simulations, the longest stretch of consecutive dry years was 7 years, and the longest consecutive stretch of wet years was 10 years.
- The driest 10-year periods identified from the set of GCM simulations contained as few as four and as many as eight dry years in a 10-year period.
- The wettest 10-year periods identified from the set of GCM simulations contained as few as four and as many as 10 wet years in a 10-year period.
- Maximum 3-day wet spells provided by the GCMs were consistently lower than those from observed data. But those from downscaled GCMs using the LOCA downscaling technique were much more closely aligned with observations than those from the direct GCM output.

More details and results of these analyses are presented in Appendix B2.

Summary and Conclusions

This chapter presents a methodology for reducing a larger set of GCMs to a subset of models that met criteria selected for California water resources planning purposes. In this methodology, the GCMs were screened using a 3-step process for global, regional, and California-specific metrics. Models that ranked lowest based on the criteria were removed from consideration. In this exercise, 10 GCMs remained after the 3-step analysis process and are currently selected for use in California water resources planning. The evaluation and model selection process should be revisited as advances are made in climate science, new updated GCMs are developed and released, and user needs change.

Chapter 3. Scenario Development for Extremes Analyses

Key Points

The following key points are called out in the body of the chapter and are given supporting explanation.

Key Point 3.1

Given the imperfect knowledge of hydrologic processes and their response to climate change and the vulnerability of populations and ecosystems to extreme events, a stress-test approach using scenarios of constructed extreme events along with analyses of vulnerability to these events, offers a vehicle to assess extremes in a planning process. Changes to the stress-test scenarios using constructed extremes can be made as knowledge gaps are filled, without changing the methodological approach. DWR planning processes can use this framework as part of its toolbox of climate change analyses.

Key Point 3.2

Understanding the underlying atmospheric and hydrologic processes that drive extremes is an important element to understanding climate change impacts resulting from those extremes. The integration of these processes that yields a flood or drought is complex. Efforts should be continued to identify knowledge gaps and pursue studies to address such gaps. The results of these efforts can then be rolled into updates of the extremes scenarios in the stress-test framework.

Key Point 3.3

Variability across different space and time scales, including decadal-scale variability, is an important part of the climate system that may not be adequately understood or captured in the observed historical record. Its incorporation into constructed scenarios of extremes for a stress-test framework has a clear tie to evaluating water system shortages resulting from droughts of various magnitudes and durations. It may also have a tie to the potential for extreme floods. Further investigation and discussion are warranted and encouraged.

3.1 Introduction

Key Point 3.1: Given the imperfect knowledge of hydrologic processes and their response to climate change and the vulnerability of populations and ecosystems to extreme events, a stress-test approach using scenarios of constructed extreme events along with analyses of vulnerability to these events, offers a vehicle to assess extremes in a planning process. Changes to the stress-test scenarios using constructed extremes can be made as knowledge gaps are filled, without changing the methodological approach. DWR planning processes can use this framework as part of its tool box of climate change analyses.

Extreme climate events are defined as the occurrence of a value of a weather or climate variable above (or below) a threshold value near the upper (or lower) ends of the range of observed values of the variable (Intergovernmental Panel on Climate Change 2012). Extremes challenge water resource systems and managers when political and socioeconomic systems do not respond adequately. They can provide an opportunity to measure how well systems are able to effectively cope with intense flood flows for example, or provide adequate water supplies in times of prolonged or extreme drought. Failure of system elements during extremes provides the motivation to improve system elements to better withstand future events. This is a form of incremental adaptation.

In a planning framework to prioritize investments for adaptation strategies to extremes, it may be difficult to identify a suitable extreme event from climate simulations directly. Lack of understanding of the role of scale, spatial and temporal variability, and key processes on the formation of extreme events are notable challenges to address. A framework that can accommodate an evolving state of knowledge of important processes and a changing landscape for the development and adoption of adaptation measures involves stress tests.

Stress tests are a way to characterize the range of climate-change extremes and both develop scenario-based analyses that consider how the state as a whole would be likely to perform if an extreme drought or flood occurred, and suggest ways to increase resilience to these events (Stern et al. 2013). Stress tests focus on identifying weaknesses and breaking points to the water system that stem from different facets of extreme events. They can help to (1) provide plausible estimates of high-impact, possibly unprecedented events utilizing climate modeling; (2) detect crucial thresholds for specific sectors and society as a whole beyond which environmental or social stability would be endangered; (3) integrate climate indicators and social consequences to assess the probability of exceeding risk thresholds; and (4) suggest new adaptation pathways to stay within bounds of tolerable risk levels (Swart et al. 2013).

Physical climate science provides important input to climate stress testing by providing the trajectory of event probabilities and potentially identifying the most exposed places. Tests consider not just historic events, but the more intense events that could occur in a changing climate, including weather and climate events occurring jointly, such as drought and heat waves, and those occurring sequentially, such as repeated storms in one location with insufficient recovery time (Stern et al. 2013). Instrumental observations, paleoclimatological proxies, and information from the historical record and climate model projections including modulations of the historical record, can identify important elements of flood and drought extremes that can be incorporated into a stress-test scenario. Within this framework, multiple scenarios can be constructed to target different aspects of vulnerability and evaluation of candidate adaptation strategies.

Another important component to stress tests is identifying the vulnerability of the people, communities, and ecosystems that may be affected by the studied extreme events; key supply chains that might be disrupted; the susceptibility of social, economic and ecological systems to harm; and the ability of the entire system to cope, respond, and recover (Stern et al. 2013). The risk of disruption from an extreme event is determined by the interactions among event severity, the exposure and vulnerability of people or things, and the ability to cope, respond, and recover from the event (Steinbruner et al. 2013).

Stress testing and the management of extreme events require understanding both physical climate science and vulnerability to the extreme event being analyzed. Additionally, stress tests can and should be informed by input and feedback between scientists and stakeholders. Through structured collaborative interaction between researchers and stakeholders, scenarios that will stress the current system can be used to investigate alternative policy or development scenarios that would likely build greater robustness and resilience into water management arrangements.

This chapter describes efforts to inform the stress-test concept as it relates to the extreme events of flood and drought for water resources planning within DWR. It focuses on the different aspects of the physical system that contribute to extreme events and offers insights into the construction of extreme-event scenarios for a stress-test analysis framework. There are many other aspects of stress tests in a planning framework that were not covered by the advisory group and remain as options for future work.

3.2 Droughts and Floods as Extreme Events

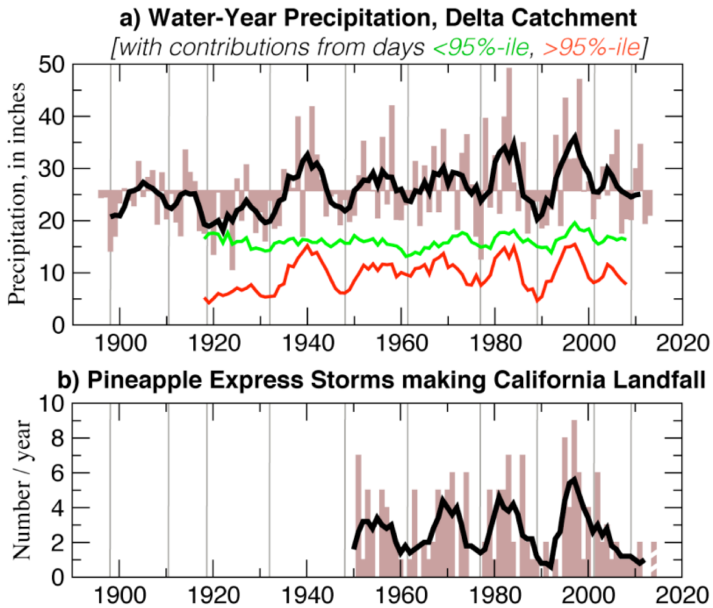
Key Point 3.2: Understanding the underlying atmospheric and hydrologic processes that drive extremes is an important element to understanding climate change impacts resulting from those extremes. The integration of these processes that yields a flood or drought is complex. Efforts should be continued to identify knowledge gaps and pursue studies to address such gaps. The results of these efforts can then be rolled into updates of the extremes scenarios in the stress-test framework.

In this section, characteristics of flood and drought extremes are identified for use in developing extremes scenarios for a stress-test framework for planning activities in California. From a water management viewpoint, floods and droughts are the opposite extremes of hydrologic outcomes to be managed via water resources engineering and operations activities. While both situations are extreme hydrologic events, they occur over different spatial and temporal scales, have different ranges of impacts and are driven by different processes that may be impacted by climate change.

On the other hand, in California, droughts and floods (or at least the large storms that often cause our largest floods) are actually very intimately connected, essentially two sides of the single “coin” of hydrologic variability and extreme. Recently, Dettinger and Cayan (2014) showed that — at the scale of DWR operations (e.g., at the scale of the Central Valley) — multiyear fluctuations in total precipitation arise almost entirely from fluctuations of water-year contributions (October 1-September 30) of the largest 5 percent of storms rather than from the contributions of the remaining 95 percent (Figure 3-1a, Table 3-1). Those multiyear fluctuations, when they trend drier than normal, correspond to drought periods. Thus, in years when California experiences its largest storms, droughts are held at bay; in years when fewer of those largest storms than normal occur, drought results. This relationship extends to a strong correspondence between the year-to-year arrivals of a particular kind of atmospheric river event (pineapple express events) and the multiyear wet-dry cycles that characterize the state’s water resources (Fig. 3-1b). In this way, the physical processes that drive the interannual-to-decadal scale variability in the number and size of these events drive the evolution of the arrival of floods and droughts to California. As such, it is important to improve our understanding of the processes that contribute to the formation and variability of atmospheric river events to better understand the implications of climate change on floods and droughts as extreme events.

In the next two subsections, each extreme is explored and important components that help characterize the extreme are identified. These components can be used to construct scenario extremes for use in a stress-test framework for climate change planning for extremes in water resources.

Figure 3-1 Water-Year Precipitation Totals in Central Valley Catchment



Notes**:**

Water-year precipitation totals (brown bars and black curve) in Central Valley catchment, 1895-present, and 5-year moving averages of contributions to totals from the wettest 5 percent of wet days (days with precipitation > 95th percentile; darker, red curve) and all other wet days (< 95th percentile; lighter, green curve), 1916-2010; and (b) numbers of pineapple-express storms making landfall between 35ºN and 42.5ºN per water year since 1948. Heavy curves are 5-year moving averages in both frames; vertical grey lines are approximate centers of persistent droughts in upper panel.

Table 3-1 Correlations of Water-Year Precipitation for the Central Valley Catchment

	Correlations with Water-Year Precipitation Totals	
	Yearly	**Five-Year Moving Averages**
Contributions from largest 5% of storms	0.92	0.96
Contributions from remainder of storms	0.67	0.50
Number of pineapple-express storms making California landfall	0.58	0.87

Notes:

The table shows correlations of water-year precipitation totals for the Central Valley catchment with total precipitation contributions from the largest 5% of storms (historically), total contributions from all smaller storms, and the numbers of pineapple-express storms making landfall each year. The closer to one the correlation is, the more closely related as the variables in question.

3.2.1 Floods

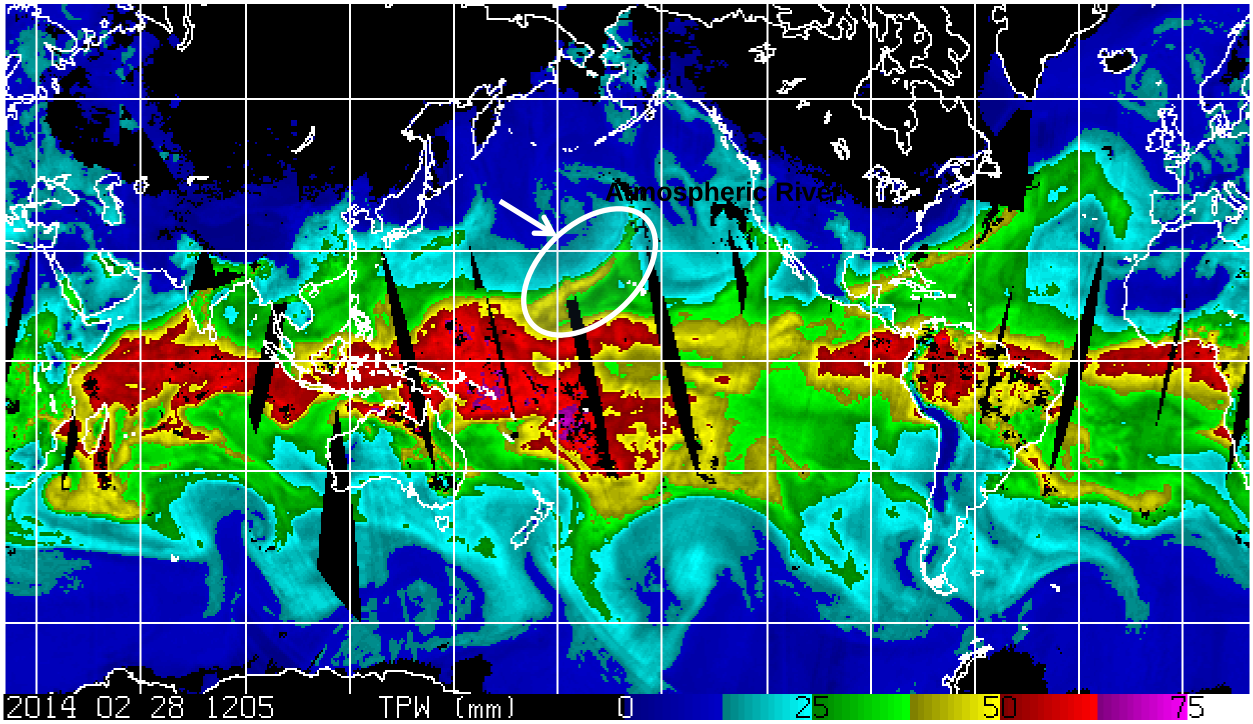
Historically, flood planning in California has followed the national practice of developing a statistical estimate of flood peak and volume from the observed data set. Design flood hydrographs reflect the appropriate return period (e.g., 100-year) of the statistical estimates and plans that are developed to protect against that threshold of flooding. The methodology relies on historical data and is not well-suited to the incorporation of climate change information.

In California, major flooding is associated with an identifiable physical process, namely atmospheric river events. Atmospheric rivers (ARs) are narrow bands of low-level, high-concentration atmospheric water vapor that extend from the tropics into the mid-latitudes (Zhu and Newell 1998). In the Pacific-Ocean-centered image of the globe in Figure 3-2, warm colors represent areas of high-concentration water vapor. Most of the reds and purples are located in the tropics where the majority of the world's atmospheric water vapor is concentrated. Extending from this large reservoir of atmospheric water vapor are narrow filaments that move into the middle latitudes, sometimes for thousands of miles. These narrow filaments are the ARs. They are thousands of miles in length yet only a few hundred miles wide. Most of the water vapor in these ARs is found in the first 15,000 feet (4,572 m) in the atmosphere.

In the image below, one of ARs extending from the tropical Pacific is highlighted. Research has found that these narrow bands of atmospheric water vapor are responsible for over 90 percent of the equator-to-pole transport of water on the globe (Zhu and Newell 1998). Research has also shown they are present with storms associated with California's largest floods (Dettinger and Ingram 2013).

For the ARs that affect California, there appear to be three main source regions: the western Pacific, the central Pacific around Hawaii, and the eastern Pacific. In fact, the storms associated with ARs originating in the central Pacific, around Hawaii, have often been called Pineapple Express storms. For large events, such as the 1997 flood, multiple source areas can feed ARs into the storm event. In large events, such as the 1986 flood, multiple AR events hit California in quick succession.

Figure 3-2 Satellite Image of Water Vapor Concentration



Notes**:** In this satellite image of water vapor concentration, warm colors represent higher amounts of water vapor. Continents are blacked out because the relationship to derive water vapor from satellite measurements only works with water as a lower boundary condition.

To that end, an atmospheric river event, or ARE, is a winter storm that includes an AR that results in heavy rainfall and high snow lines, and may result in flooding if the duration of the event is long enough and watershed conditions are suitable for runoff generation. Certain thresholds of antecedent conditions in the watershed affect the size of the flood flows in California. Characteristics of an ARE can be evaluated for change associated with climate change. These characteristics of an ARE can be used in flood management planning and the construction of flood-event scenarios for stress testing. These characteristics are described below.

Recent research has helped identify and define characteristics of AREs associated with major flooding in California. From analysis of that work, the following ARE characteristics appear to have the most promise in serving as a basis for planning, forecasting, and warning activities. These characteristics are (1) atmospheric water vapor in an atmospheric river, (2) winds associated with the winter storm dynamics that drive the AR into California, (3) the freezing elevation of the storm, and (4) the duration that these conditions prevail over California's topography. Each of the characteristics is further described below.

The first two characteristics, water vapor and winds, can be combined into a parameter called moisture flux. A minimum threshold of at least 1 inch of atmospheric water vapor and winds of at least 10 feet per second are needed to generate the necessary 10 inch-foot/second (ifps) or .077 meters squared per second of flux needed to produce heavy rainfall (Neiman et al. 2009). The moisture flux characteristic can be assessed under historical conditions and in the future projections from climate change models. Initial work in this area has been carried out by Dettinger et al. (2011).

The next characteristic is the direction of impact on the mountainous watersheds. The watersheds draining the mountains of California each have their own unique topographic distribution. Because of this, different orientations of ARs produce different orographic enhancements of precipitation (Ishida et al. 2014). For example, southwesterly flow is needed for excellent orographic rainfall production in the Feather River watershed, while southerly flow produces higher orographic rainfall totals in the watersheds draining into Shasta Reservoir. The direction of impact characteristic is individual to each watershed and may constrain the size of a system-wide flood resulting from a single ARE. Further work is needed to articulate the climatology of angle of impact of an ARE from historical storms and potential future storms. The role of topographically induced flows, such as the Sierra Barrier Jet, also need to be articulated as it relates to creating multiple favorable angles of impact and extends the region of orographically induced precipitation.

Freezing elevation defines how much of the watershed will contribute to direct runoff processes. In the northern Sierra, some observed extreme events have yielded rainfall to the top of the watershed. The higher southern Sierra has yet to see an event with this characteristic. That may change in the future as a warming climate is expected to raise the freezing elevation associated with these storms. A recent study by the United States Army Corps of Engineers examined the role of increased watershed area resulting from warmer temperatures for a collection of historical and scaled historical events (U.S. Army Corps of Engineers 2015). Further work is needed to explore this relationship and articulate its construct in flood-scenario construction.

The magnitude of runoff from AREs may be related to the duration of the event relative to the time of concentration of the watershed. The duration of AR conditions is the time when the moisture flux and associated rainfall exceeds the minimum threshold. For fast-moving storms, the duration of AR conditions over the watershed or parts of the watershed are relatively short, which in turn limits the runoff from the event. However, if the system stalls over a watershed or has dynamical characteristics that broaden the width of the AR which extends the duration, the potential for extreme runoff conditions increases. Further work is needed to characterize the climatology for the duration of AR conditions for given watersheds in California.

While AREs can be related to extreme precipitation events, the translation from precipitation to runoff depends heavily on the condition and structure of the watershed. The amount of snow, soil, and vegetation conditions, as well as the amount of soil and reservoir storage in the upper watershed, acts to modulate the rainfall into runoff. The size and shape of the watershed are also important in how the runoff from the different parts of the watershed come together to form the outlet flood hydrograph. Specification of antecedent conditions for the flood scenarios for stress-test analyses need to be made, and a decision needs to be made as to what changes would be in play with climate change. Further work is needed in this area.

Over the course of the 21st century, the state of the climate system is expected to change leading to a warmer world with potentially more extreme weather events. The State of California has determined that such change should be incorporated into its planning efforts and adaptation strategies should be developed and pursued. For the Sacramento/San Joaquin River basins, the impacts of climate change include elevated temperatures that will affect the location and size of the seasonal snowpack. Vegetation changes can affect the timing and amount of runoff from the hillslopes into the main stream channels. While seasonal and annual totals of precipitation may change, it is the changes in size, character, and duration of

AREs (Dettinger 2011) that will affect the flood flows making their way through the system into the Delta, where sea level rise will affect the ability of the flows to drain out to the ocean. As noted above, further work is needed to develop ARE characteristics so that they can be used to develop flood scenarios for stress-test analyses for planning applications. Further work on the observation of ARE characteristics will help in operations, forecasting, and warning activities. Future advisory groups may wish to weigh in on the continued work in this area.

3.2.2 Drought

Key Point 3.3: Variability across different space and time scales, including decadal-scale variability, is an important part of the climate system that may not be adequately understood or captured in the observed historical record. Its incorporation into constructed scenarios of extremes for a stress-test framework has a clear tie to evaluating water system shortages resulting from droughts of various magnitudes and durations. It may also have a tie to the potential for extreme floods. Further investigation and discussion are warranted and encouraged.

Unlike their characterization of floods, climatologists call drought a "creeping disaster" because its effects are not felt at once. While difficult to define, a drought can be loosely described as an abnormal water deficit. Such a deficit is expressed as a deviation from the long-term quantity of water typically experienced. The normal water amount found at one location will rarely be the same amount found at other locations, which is why the definition of drought is always specific to a locale. Moreover, the hydrologic cycle has a number of different flow and reservoir water components, such as precipitation, runoff, soil moisture, streamflow, surface storage, and groundwater storage/recharge. Although these water-cycle components are related, they are not identical. Because one component could have a surplus, while at the same time another could reflect a deficit, drought can be defined relative to a specific component. A meteorological drought relates to a precipitation deficit, a hydrological drought is associated with deficits of streamflow or groundwater supply, and an agricultural drought is concerned with soil moisture deficits.

Observations from the instrumental record, paleo proxies, and projections from climate change models all can be used to inform characteristics that help define drought. Some of these characteristics are explored below, based on information presented during advisory group meetings. Further work is needed to shape these elements into characteristics that can be used to construct extreme scenarios for stress-test analyses for water resources planning activities.

As noted above, drought can be described with different facets related to the source and location of water shortage from long-term normals or averages. Nonetheless, for the different types of droughts, similar characteristics can be described to characterize the extreme nature of those conditions. Developing specific characteristics that can be used to create potential drought scenarios was not discussed in any detail by the group. A representative from the California Water Plan (CWP) team presented the methodology used for the CWP. The Water Plan team creates an analysis scenario by taking critical drought sequences in the historical record and adding an additional extreme year. Other groups in DWR simply use the historical time series in their analyses. As noted below, that approach misses some important elements of temporal variability. As a result, drought characteristics that can be articulated for present and future conditions in an extreme scenario are an area for future development. The advisory group spent more time on the different scales of variability and its impact, which are described below.

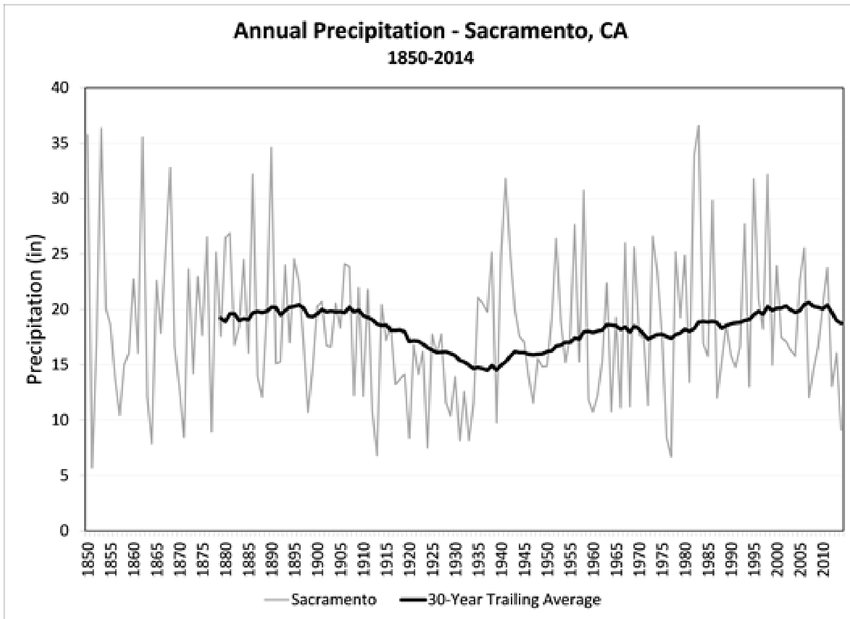
California is constrained in its characterization of drought by the relatively short observational record. Data for precipitation and surface-water runoff quantities for local watersheds are available from DWR and other State entities, and from federal entities such as the U.S. Geological Survey. But most rain and stream gauges in California were installed in the latter half of the 20th century. The information below demonstrates that this is insufficient time to detect short-term trends, much less longer-term climate signals, and evaluate different scales of variability.

In western North America, paleoclimate archives reveal that the 20th century does not capture the complete range of drought variability that has transpired over the past 1,000 years (Meko 2007). Examples include abrupt shifts to large-scale drought, which were more intense and longer lasting than the 1930s Dust Bowl drought years, and decade-scale long droughts occurred on average twice per century (Woodhouse and Overpeck 1998). Tree ring records of drought in the western United States show abrupt, long-lasting mega-droughts that came on rapidly and covered most of the region for more than a decade (Steinbruner et al. 2013).

Additionally, Ault et al. (2014) point to instrumental and paleoclimate data in semi-arid regions, indicating that natural hydroclimate fluctuations occur at both low (multi-decadal to multi-century) and high (interannual) frequencies. Because state-of-the-art global climate models do not capture this characteristic of hydroclimate variability, the models may underestimate the risk of future persistent droughts. Their findings suggest that a multi-decadal drought could present major challenges to water resources in California, and are important to consider as adaptation and mitigation strategies are developed to cope with the regional impacts of climate change.

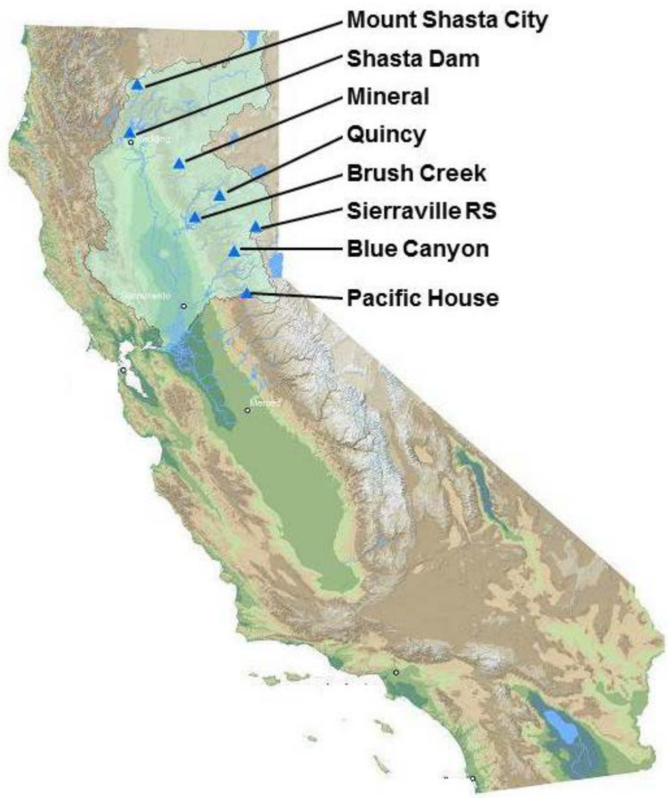
One of the very few long term rainfall records that extend back to the 19th century is the annual precipitation record for Sacramento. Starting in 1850, the Sacramento gauge record provides a 164-year glimpse into California’s climate past. Figure 3-3 presents Sacramento’s annual rainfall trace from 1850-2014.

Figure 3-3 Annual Precipitation, Sacramento, California, 1850-2014



Data sources: California Department of Water Resources 2014a

Figure 3-4 Northern Sierra 8 Station Index Gage Locations



The extreme variability year to year is obvious upon visual inspection, with the highest annual amounts about six times the lowest annual recorded precipitation. Interestingly, Sacramento's volatile record exhibits an extended period of relative quiet. For 50 years, from 1890 to 1940, Sacramento experienced both lower rainfall and lower variability.

The early 20th century rainfall "trough" is clearly seen in the 30-year trailing average, as plotted in Figure 3-3 by the heavy dark line. In 1896, the trailing 30-year average peaked at 20.42 inches (51.87 centimeters [cm]), then fell steadily to the 1937 minimum of 14.51 inches (36.86 cm). Over the next 70 years, Sacramento rebounded sufficiently for the 30-year average to recover to a peak of 20.63 inches (52.40 cm) in 2007. What is disturbing is the significant decline in the 30-year average precipitation in Sacramento since the 2007 peak. This drop is as steep or steeper than any decline over a similar period in well over a century. Developing adaptive capacity to this decadal-scale variability appears to be an important element of extremes planning processes.

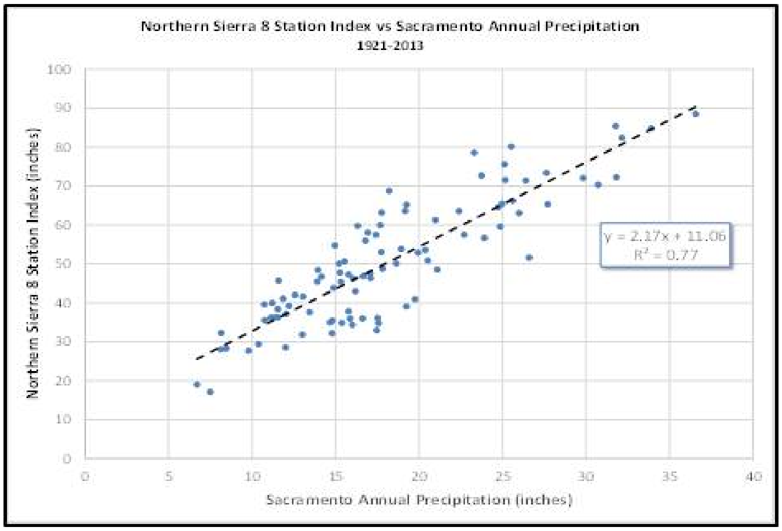
DWR monitors precipitation at eight locations in a 15,700-square-mile area (40,663 square kilometers) in the northern Sierra Nevada Mountains (Roos 2009). The locations of the eight precipitation gauges are shown in Figure 3-4. DWR has maintained the Northern Sierra 8 Station Index since 1921.

Figure 3-5 presents a scatterplot of Sacramento's annual precipitation versus the Northern Sierra 8-Station Index during the overlapping period of record, 1921-2013. Sacramento's annual rainfall and the Northern Sierra 8-Station Index are highly correlated. Using the linear trend line shown on Figure 3-5, Sacramento's annual precipitation explains about 77 percent of the variance in the 92-year record on 8-Station Index values.

Such strong correspondence between the annual rainfall in Sacramento and conditions in the Northern Sierra since 1921 suggests that the Sacramento annual rainfall is a reasonable indicator of conditions throughout the Northern Sierra. Given this strong correspondence, it is likely that the Northern Sierra was relatively wet during the last half of the 19th century and became increasingly dry during the first half of the 20th century, before rebounding to a relatively wet condition over the last 70 years.

The recent positive wet trend is a strong one. At the 2007 peak of the 30-year trailing average (20.63 inches, or 52.40 cm), Sacramento's "climate" was 42 percent wetter than the previous hydroclimate minimum in 1937 of 14.7 inches (37.34 cm). To restate, for three decades, 1978-2007, Sacramento and by extension the Northern Sierra received 42 percent more precipitation than during the 3-decade period from 1908-1937. Such multi-decadal variability needs to be captured in drought scenarios for water resources planning.

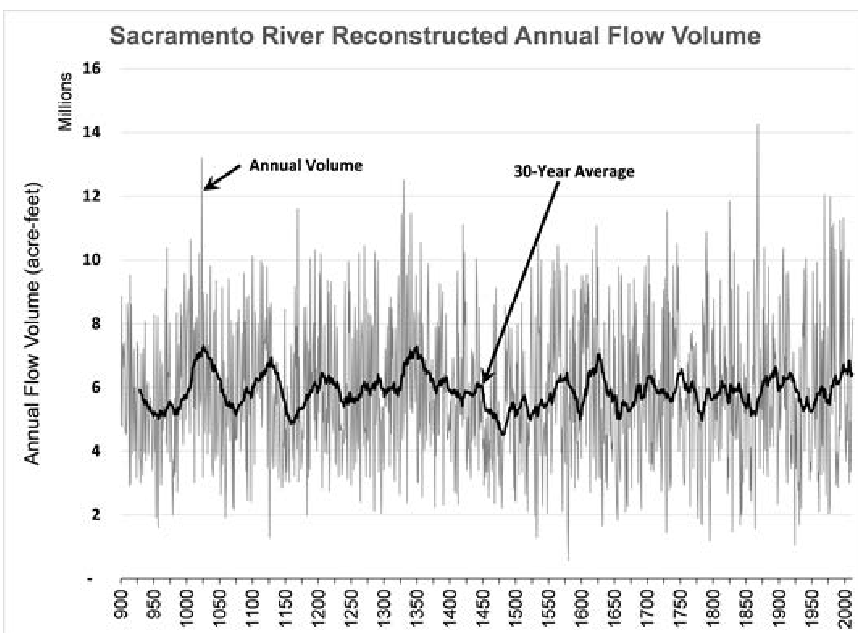
Figure 3-5 Correlation between Sacramento Annual Precipitation and Northern Sierra Precipitation 8-Station Index



Data source: California Department of Water Resources 2014a and 2014b

Tree-ring data are useful indicators of past climate, for which direct observations of rainfall or streamflow are unavailable. DWR recently commissioned a research project to reconstruct hydroclimates for the Klamath, San Joaquin, and Sacramento river basins from tree-ring data (Meko et al. 2014). The project reconstructed unimpaired streamflows in the Sacramento River basin for 1100 years, 900-2010 A.D. (See Figure 3-6.)

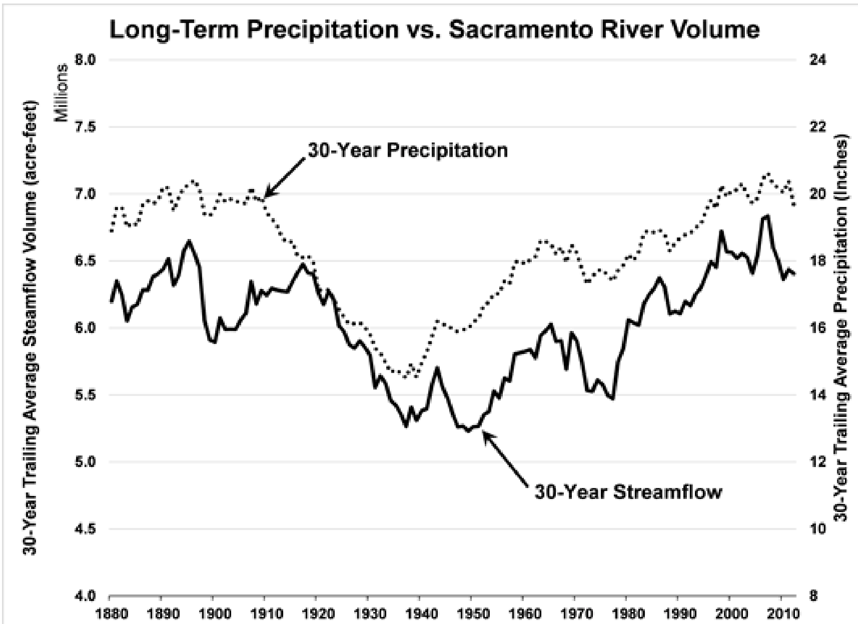
Figure 3-6 Reconstructed Sacramento River Streamflows



Source: Meko et al. 2014

The 30-year trailing average annual streamflow volume is plotted on Figure 3-6 as the heavy black line. Throughout the 1100-year record, Sacramento streamflow drifted back and forth from wet regimes to dry and back to wet again. The 30-year trailing average of reconstructed Sacramento River annual volumes follows a pattern that is very similar to the 30-year trailing average of Sacramento's annual precipitation. (See Figure 3-7.) This result is not unexpected, as streamflow volumes would likely follow persistent precipitation patterns.

Figure 3-7 Comparison between Long-Term Sacramento Precipitation and Sacramento River Volume Trends



An important insight from Figures 3-3 and 3-7 is the strong upward trend in rainfall from the 1920s to 2000. This progression from dry to relatively wet occurs in the period of most rain and streamflow records in California. A consequence of this is that most of northern California's observed record only captures the upward trend. Current observations almost completely miss the drying trend from the 1890s to the 1930s.

Looking again at the long-term trends in streamflow volumes (30-year trailing averages in Figure 3-6), we find that repeated wet/dry cycles appear throughout 1100-year reconstructed record. The 30-year trailing average annual streamflow volume maxima are often 25-50 percent greater than preceding minima. Often the transition from a hydroclimate maximum to a hydroclimate minimum can occur relatively quickly, on the order of three to four decades.

The reconstruction record of Sacramento River runoff from tree-ring data for DWR suggests that the drought from 1929-1934 was the most severe in the 420-year reconstructed record from 1560 to 1980. The data also suggested that a few droughts prior to 1900 exceeded three years, and none lasted over six years, except for one period from 1839-46. However, a 1994 study of relic tree stumps rooted in Mono Lake, Tenaya Lake, West Walker River, and Osgood Swamp in the central Sierra Nevada suggests that

California sustained two epic drought periods, extending over more than three centuries (Stine 1994). The first epic drought lasted more than two centuries before the year 1112; the second lasted more than 140 years before 1350. A conclusion drawn from these investigations is that under climate change, California may be subject to droughts more severe and more prolonged than anything witnessed in the historical record. That possibility underscores the need to develop constructed drought scenarios that include such magnitudes and durations (California Department of Water Resources 2000).

3.3 Extreme Scenarios for Stress-Test Analysis

The risk of an extreme event is assessed through an analysis of event probability and exposure. Additionally, risk requires a vulnerability analysis "to understand what people and sectors may be most affected by the extreme, why these impacts occur, and if these relationships are changing over time" (Hayes et al. 2004). Results can then be used to guide pre-event planning and mitigation programs that diminish the risk of future impacts, and in turn lessen the burden placed on response-oriented management.

Vulnerability analysis begins with acquiring data on first, second, third, and higher magnitude of order impacts. The causes of impacts can then be explored by "tracing outwards from each impact the multiple environmental, social and economic underlying factors that contribute to the resulting impacts" (Hayes et al. 2004). Significant public involvement is essential during the exploration of impact causality (National Drought Policy Commission 2000). The results of impact and vulnerability assessments are then used for developing and prioritizing targeted, long-term planning and mitigation programs.

3.3.1 Flood Scenarios

The characteristics of AR events identified above can be used to create a significant design storm or design storm series for the flood extreme scenarios to drive the stress-test framework to use in flood planning. A variant of this has already been completed by the U.S. Geological Survey (USGS) through their ARkStorm project (Porter et al. 2011). Within the context of evaluating flood vulnerabilities under present-day climate, the USGS ARkStorm project constructed a worse-than-any-in-the-20th-century storm and flood scenario for emergency-preparedness exercises and planning, by stitching together two historical storms (from January 1969 and February 1986) end-to-end in rapid succession so that the sustained deluge was longer (23 days) than any since the "Great Flood" of 1862 (40-plus days). Similar stitching strategies can be employed with hydroclimatic conditions from detailed observations from the instrumental period, from less-detailed prehistoric reconstructions, and from past and future periods among projections used in their climate change assessments.

Care needs to be taken to preserve as much of the internal climatic consistency (and natural variation) in the resulting constructed scenarios as possible. In the ARkStorm scenario, this was accomplished by carefully choosing the days when the two historical storms were blended into a single storm in such a way that they were as meteorologically consistent (within about a day's worth of atmospheric evolution of each other) as possible (Dettinger et al. 2012).

Work continues within DWR to develop AR-based flood planning scenarios that incorporate potential changes in storm characteristics associated with climate change. As this effort matures and vulnerability analyses are completed, a stress-test framework to inform flood management planning can be developed and implemented.

3.3.2 Drought Scenarios

To explore vulnerabilities to multi-year drought, the Colorado River Severe Sustained Drought Study of the early 1990s (Tarboton 1995) was a multi-agency assessment of the probable supply and environmental, economic, and legal impacts of a hypothetical drought, based on the driest 20-year period (AD 1579-1600) in the past 400 years as ascertained from tree-ring reconstructions of Colorado River flows. In the case of multi-year or multi-decade drought, a possible stress-test strategy would draw on the observation by Malamud-Roam et al. (2007). That study establishes that the mega series of drought during the Medieval period in the Sierra Nevada was — for the most part — not a result of drought years that were well outside the historical range, but rather years that corresponded to long periods when historic-level drought occurred with unprecedented and significantly high frequency. This observation means that examples of plausible prehistoric mega-drought conditions can be constructed by resampling the hydroclimatic conditions from the modern observation era to purposefully exaggerate the frequency of the worst historical drought conditions. This method of drought-scenario construction, in turn, means that modern, observation-based climatic sequences, at daily levels, can provide raw materials to generate temporally detailed and meteorologically, internally consistent hydroclimatic scenarios of mega-drought conditions, such as those in the region's distant past.

In California, there were 11 recognized, statewide droughts between 1895 and 2011, each lasting at least two years (California Department of Water Resources 1978, 1993, 2010; USGS 2004). The statewide mean annual precipitation during these events was 17 inches, or 76 percent of the long-term mean. Four of these events lasted two years, and two lasted six years. Precipitation values, expressed as a percentage of the long-term mean, ranged from a mild intensity drought with 92 percent of the mean, down to 57 percent for the severe 1976-1977 drought. The 1929-1934 drought established the criteria commonly used in designing storage capacity and yield of large Northern California reservoirs. For the nine most-recent droughts for which runoff quantities are available, precipitation was 75 percent of the mean and the runoff was 60 percent. Note the stronger reduction in runoff as a response to the relatively modest reduction in precipitation.

Socio-economic impacts of drought can vary depending on sector, prioritization of the use of limited supplies, and efforts to collaborate to mitigate impacts. The scale and number of impacts depend on the length and severity of drought. In general, there will be less water available for agriculture, municipalities, and ecosystems. How much is available depends on past and current management, on water rights, on location, on land use, size of agricultural operation and type of crop grown, size of municipality, and whether there are multiple sources of water for consumption, as well as other factors. Specific impacts may include:

- Reduction in surface water flows and imported water supplies.
- Drying up of wells, wells needing to be deepened, or new wells needing to be sunk.
- Decline in groundwater-level as a result of increased pumping.
- Reduction in hydropower generation.
- Increase in health and safety problems, such as running out of water for drinking, sanitation and firefighting.
- Increase in wildfires.
- Reduction in water quality.

Historically, typical responses to drought periods would be local agencies curtailing water use, pumping more groundwater, fallowing land, and executing water transfers. Requirements for planning for drought are few in California, with some specifications found in urban water management plans, groundwater management plans, and integrated regional water management plans.

A series of scenarios for extreme drought events at a variety of scales, and that encompass both physical and social dimensions, could assist in developing robust adaptation strategies to cope with significant drought in a changing climate where temperatures will be warmer and hydrologic relationships between precipitation and runoff will change. Further work needs to be done to frame the characteristics desired to test select vulnerabilities and develop the stress-test framework to evaluate candidate adaptation strategies.

3.4 Gaps and Areas for Future Work

A stress-test framework using constructed extremes scenarios offers a way for DWR to analyze extremes impacts that incorporate climate change. A complete exploration of the methodology was not completed in this iteration of the CCTAG. Instead, the methodology was arrived at through a set of evolving discussions of incorporating different facets of change and variability into floods and drought analyses. This chapter summarizes these discussions and attempts to provide context of how this synopsis would fit in a stress-test framework.

Aspects of ARs were identified that could be used to build design storm scenarios for flood analyses. Different aspects of variability at different time scales were identified that could be used in the construct of drought scenarios. Examples of both flood and drought scenarios in other studies were identified.

Areas yet to be covered include creating a guide to developing stress tests for use in flood and drought planning within DWR programs, identifying drought metrics that can be tied to climate change and used to construct a drought extreme scenario, and identifying planning metrics to target in the development of extremes scenarios. These are areas for further development and exploration by DWR and any future advisory group.

3.5 Summary and Conclusions

The hydroclimate of California is inherently unstable and unpredictable. Data suggest that California's climate persistently drifts from wet to dry and wet again, persisting in a given state for decades or more at a time. Annual rainfall volumes for Sacramento and possibly the Northern Sierra may vary as much as the 40-percent-higher 2007 hydroclimate maxima than for the 1937 minima. These variations have been linked to the number of AR events that, in their extreme state, cause extensive flooding.

The period from which most of California's hydroclimate observations are taken is marked by a strong upward trend in annual precipitation volumes. Short observational records miss most, if not all, of the preceding four-decade drying trend. That most observational records miss a major component of the California's wet/dry cycle suggests that analyses and water management strategies that use these records may be seriously compromised.

Water supply pressures in California resulting from increasing population over the past century may have been mitigated or masked by the coincident upward precipitation trend. Of concern is the significant decline in the 30-year average precipitation in Sacramento over the last 10-15 years. This drop is as steep or steeper than any decline over a similar period in well over a century. It is conceivable that California is already more than a decade into a multi-decade drying trend. If this is the case, understanding linkages between climate risks and water management is critical to meeting the demands of 50 million people with perhaps 30 percent less precipitation than today, with demands modulated by rising temperatures.

The cyclic features of wet/dry eras in California's climate are significant and important to understand. It is also important to understand how these features will change as a result of climate change. It is critical that these features are explicitly recognized in the analytic tools used to develop adaptive strategies for water management in California.

The wet/dry cycles have apparently existed and persisted long before the impacts of modern man. They are a natural part of California's climate history. Looking forward, we need to understand the dynamical causes of these multi-decade features in order to adequately incorporate them into anthropogenically induced climate-change impact analyses.

Climate extremes can lead to significant disruptions in societies or political systems. It is suggested that the State prioritize further research to understand exposure and susceptibility to harm from droughts and floods, plus current and potential adaptation approaches. Knowledge gained from such research can be incorporated into updates of stress-test scenarios used in flood and drought planning activities.

Chapter 4. Downscaling

Key Points

The following key points are called out in the body of the chapter and are given supporting explanation.

Key Point 4.1

Because global climate models (GCMs) yield coarse resolution output, “downscaling” is conducted to provide the spatial details of climate differences and variability that drive most of the watersheds, rivers, and systems of California water for use in local-to-small regional assessments and applications. GCMs are increasing in their spatial resolution, but the level of spatial detail they will provide is likely to be 50 kilometers (km) (30 miles [mi]) or coarser throughout the next decade. Thus, the California Department of Water Resources (DWR) will rely on downscaling as an integral part of its climate change analyses for the foreseeable future.

Key Point 4.2

Dynamical downscaling is developed from the output of full-physics classes of models to represent the influences of topography and land-water differences in far greater detail than the global models. Dynamical modeling can provide a full suite of climatic and hydroclimatic variables as outputs. In practice, however, the dynamic models also have limitations: They depend on parameterized versions of physical processes developed from historical observations, produce biases that are generally adjusted using statistically based bias corrections, and are challenged in producing large numbers of century-long climate simulations because of high computational and storage requirements.

Key Point 4.3

Statistical downscaling has the advantage that downscaled products are readily available or can be produced for a large number of climate change scenarios from different global models and under a variety of different assumptions. That said, statistical downscaling hinges on the assumption of “stationarity,” wherein the model is developed from relationships of historical large-scale to historical finer-scale variations, and depends on the quality of historical observation data used to develop the statistical-downscaling methodology.

Key Point 4.4

Statistical-downscaled products are acceptable to meet immediate needs, as well as for continuity, consistency with efforts by agencies other than DWR, and convenience. Nonetheless, either new statistical methods or, preferably, dynamical downscaling will be needed to address many issues that DWR is likely to face in the future.

Key Point 4.5

Both statistical and dynamical downscaling have strengths and weaknesses. The best downscaling approach depends on the specific application for which the downscaled data will be used.

Key Point 4.6

DWR should consider designing or supporting an intercomparison of downscaling methods and sources that reflects its particular applications and needs.

Key Point 4.7

All downscaling efforts ultimately draw on, or are justified by, comparisons to real-world observations. Thus, frequent and regular observations of a suite of climate and hydrologic variables at many locations are an enabling factor in downscaling success, whether by statistical or dynamical methods. DWR should develop an appraisal and plan for the readiness of the networks of observations that underpin its climate-change downscaling activities.

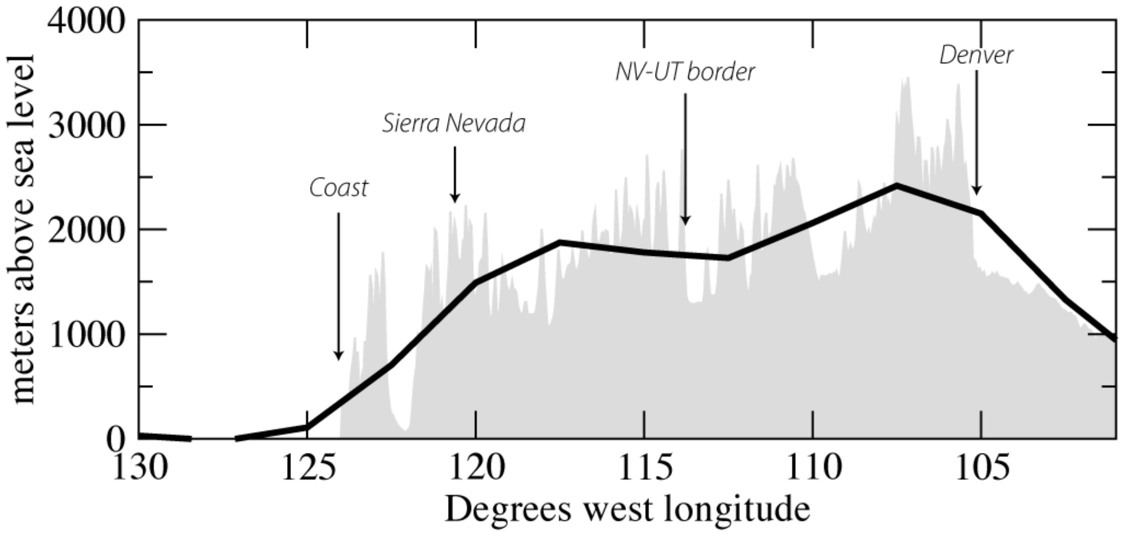
Introduction

Key Point 4.1: Because global climate models (GCMs) yield coarse resolution output, "downscaling" is conducted to provide the spatial details of climate differences and variability that drive most of the watersheds, rivers, and systems of California water for use in local-to-small regional assessments and applications. GCMs are increasing in their spatial resolution, but the level of spatial detail they will provide is likely to be 50 kilometers (km) (30 miles) or coarser throughout the next decade. Thus, the California Department of Water Resources (DWR) will rely on downscaling as an integral part of its climate change analyses for the foreseeable future.

Numerical climate-change projections provide the raw materials for most assessments of vulnerabilities and responses to climate change by DWR and others. Today, the projections are typically made by simulating climatic variations and changes in "free" simulations by global, coupled atmosphere-ocean-land models of climatic responses, with only the astronomical solar inputs, as well as greenhouse gas and aerosols concentrations of the atmosphere, imposed as time-varying boundary conditions. These models represent the climate as discretized on grids and layers that span the globe, with the geographic distribution of grid-cell centers typically separated by about 1.0 to >2.5 degrees of latitude and longitude. At the latitude of California, a degree of latitude and longitude equals about 100 km (60 miles). At 2.5-degree resolution, the Sierra Nevada does not appear as a separate mountain range from the great western North American mountain belt, the Coastal Ranges are nonexistent, and the highest peak along the latitude of Red Bluff (40 degrees North latitude) only rises to about 1700 meters (approximately 5,600 feet) above sea level in the Sierra Nevada (Figure 4-1). Land-surface slopes and land-water contrasts are likewise almost entirely muted. No river catchment in California spans more than a few of the global-model grid cells, and most are much smaller than any one grid cell. Thus, some way to interpolate or project global-model outputs to much higher spatial resolutions is needed for practical assessments and modeling of the climate influences at scales that matter most for DWR.

Climate projections at this coarse resolution offer little immediate information about the spatial details of climate differences and variability that drive most of the watersheds, rivers, and water systems in California, which commonly differ significantly over distances of kilometers or less. As a consequence, various procedures collectively called "downscaling" are applied to develop more highly spatially resolved versions of the climate changes simulated by the global models for use in local–to-small regional assessments and applications. Two broad purposes motivate downscaling. First, increasing the (apparent) resolution of climate simulations and projections is the most obvious aspect of downscaling. GCMs (as well as more highly resolved local-to-regional climate models) are approximations of the real climate systems, and they have been calibrated to reflect the real world. Although those calibrations focus on making the simulated global-scale patterns and seasonalities as realistic as possible, they do not specifically attempt to ensure that the simulated climate of California is as realistic as possible. For that reason, and speaking to its second purpose, downscaling also typically involves steps to correct for bias (long-term average errors) in the locally simulated climate to reduce or eliminate errors from the large-scale climate model outputs.

Figure 4-1 Average Elevations at Each 2.5º x 2.5º Grid Cell in the NCEP-NCAR Reanalysis Fields for Transect at 40 Degrees North Latitude



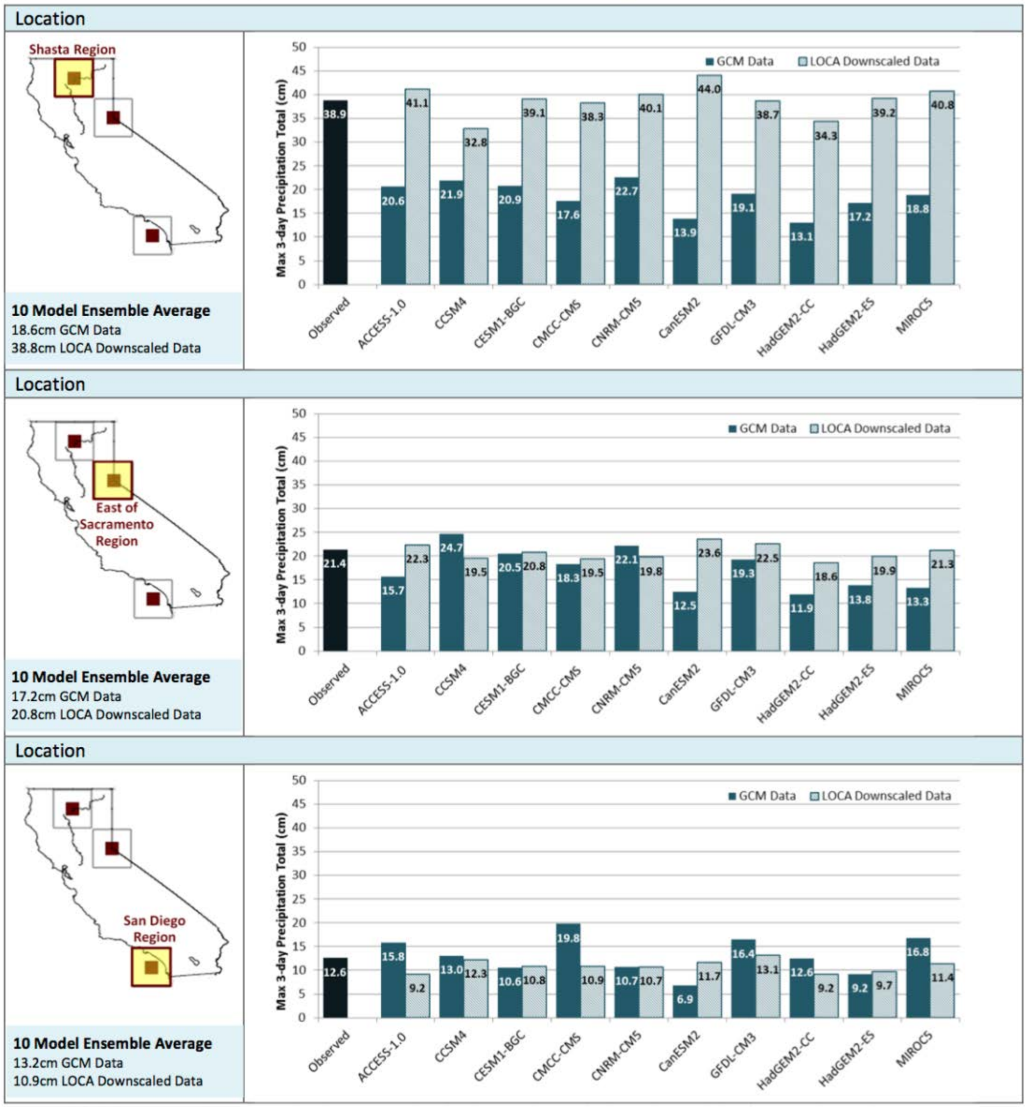
Notes:

NCEP = National Centers for Environmental Prediction, NCAR = National Center for Atmospheric Research. Average elevations are represented at each 2.5º x 2.5º grid cell in the NCEP-NCAR Reanalysis fields (black curve) and from a 25-meter (80-foot) digital elevation model (grey shading), along the latitude band centered on 40ºN, as an example of the topographic smoothing that occurs in global-model scale fields and outputs.

A sense of the benefit that comes from downscaling (along with bias corrections) is offered by the comparisons in Figure 4-2. In this diagram, the wettest 3-day totals of precipitation at three sites in the state, in historical-period climate-model simulations with and without downscaling, are compared with observed values. The GCM values deviate more from observations in each case than do the downscaled version (LOCA, a downscaling method that is discussed below). Most notably, for the grid cell over the Shasta drainage, the wettest extreme events are substantially muted, at least in part, because of the lack of topography and orographic enhancements of precipitation present in the global models.

Downscaling has been pursued in California (Pierce et al. 2013) and elsewhere by statistical- and dynamical- (numerical-modeled) downscaling methods. Dynamical downscaling (Mearns et al. 2009) uses projected global-model variables (outputs) as initial and boundary conditions for simulations by limited-area, high-resolution models of local-to-regional climate. Statistical downscaling (Wilby et al. 1998) first extracts or assumes statistical relationships among historical high-resolution observations of climate variables (at stations or in interpolated gridded fields) and global-model variables, using a variety of methods. Then, these historically derived relationships are applied to other past or future outputs of the same global-model variables to estimate what the high-resolution details of future climate might look like. These two approaches are discussed in turn, below.

Figure 4-2 Wettest 3-Day Precipitation for the Simulated Historical Period (1950-1999) by 10 Recommended Global Climate Models



Notes:

GCM = global climate model, LOCA = Localized Constructed Analogue downscaling method. Observed data from Livneh 2013 for 1950-2013. LOCA data are preliminary and are subject to revision.

Comparisons are of the wettest 3-day precipitation totals observed historically (black) with the extremes simulated by 10 GCMs (dark blue) and the same simulations after statistical downscaling and bias correction (pale blue) by the LOCA downscaling method (Pierce et al. 2014) at three locales in California. The LOCA downscaling method is discussed later in this chapter; see chapter 2 for details of climate models and model selection. For GCM background information and affiliated research institutions, see CMIP5 Coupled Model Intercomparison Project at http://cmip-pcmdi.llnl.gov/cmip5/availability.html.

Dynamical Downscaling

Key Point 4.2: Dynamical downscaling is developed from the output of full-physics classes of models to represent the influences of topography and land-water differences in far greater detail than the global models. Dynamical modeling can provide a full suite of climatic and hydroclimatic variables as outputs. In practice, however, the dynamic models also have limitations: They depend on parameterized versions of physical processes developed from historical observations, produce biases that are generally adjusted using statistically based bias corrections, and are challenged in producing large numbers of century-long climate simulations because of high computational and storage requirements.

One of the two main downscaling approaches is *dynamical downscaling***,** which is based on the three-dimensional numerical modeling of hydrodynamic equations and thermodynamic equations of the atmosphere (hence, conserving mass, momentum, and energy conditions) of the studied/modeled region under initial and 3-dimensional evolving boundary conditions that are provided by the Atmosphere-Ocean General Circulation Model/Earth System Model (AOGCM/ESM) simulations.

Downscaling of coarse, historical reanalysis climate data, the historical AOGCM/ESM simulations, or the future AOGCM/ESM climate-projection simulation results by dynamical downscaling, is an ever more feasible option for water resources applications, such as those being tackled by DWR. Although the 3-dimensional simulation of the regional atmospheric conditions by the dynamical-downscaling approach is computationally intensive, the emergence of cluster computing technology has reduced many of the practical limitations from the required intensive computations. Dynamical downscaling of coarse-resolution climate data by means of a numerical regional climate model, such as the Mesoscale Model (MM5) or the Weather Research and Forecasting Model (WRF), can be accomplished over the whole region of California, or over Northern or Southern California, or at specified watersheds of California. The dynamical downscaling of 15 100-year 21st-century climate projections from several different AOGCMs/ESMs, under various emission scenarios for the entire state of California at 9-km (5.5-mile) spatial grid resolution at hourly time intervals, can now be completed in about 18 months. If the primary focus is a limited set of watersheds, such as Shasta, Trinity, Feather, Yuba, and American, then 15 100-year 21st-century AOGCM/ESM climate projections could be dynamically downscaled over all five watersheds at 3-km (<2-mile) grid resolution at hourly intervals within 18 months. The output of the dynamical downscaling of AOGCM/ESM simulations provides not only the temperature and precipitation, but also radiation fluxes, humidity, and 3-dimensional wind fields at time resolutions as short as one minute (typically, one hour) and at spatial resolutions as fine as 1 km (0.6 mile), if needed.

A distinct advantage of dynamical downscaling is that it resolves in detail the effect of local topography (especially the steep terrain of mountainous regions) and local land-surface conditions on local atmospheric conditions. Consequently, it adds new information on the atmospheric conditions at the local watershed scale beyond that in the AOGCM/ESM simulations. Climate change will not occur in California in isolation from other ongoing changes. Coupled ocean-atmosphere regional, dynamical models are still in relatively early phases of development and testing (Putrasahan et al. 2013; Li et al. 2013), and long or multiple regional simulations have not come available. Aside from ocean-atmosphere processes, climate change impacts on California water resources will also occur in conjunction with changes in land-use, land-cover, and water-use patterns. Changes in land surface conditions can affect the climate at regional and local scales. To be able to model such impacts, it will be necessary to utilize coupled atmospheric-land hydrologic, hydroclimate models (Kavvas et al. 2011; Chen et al. 2011;

Shaaban et al. 2011; Kavvas et al. 2013), because statistical downscaling (to be discussed in the following section) cannot capture or track land-change influences. Such a coupled modeling approach is able to resolve the 2-way interaction between the atmosphere and the land surface through the atmospheric boundary layer that will evolve under the changing atmospheric and land-surface conditions through time during the 21st century. Consequently, the ultimate approach to the assessment of the impact of the simultaneous change in climate and land-surface conditions on the water resources of California would be a dynamical-downscaling approach that uses coupled atmospheric–land-surface–hydrologic–hydroclimate models.

Many climate variables, in addition to the commonly provided temperature and precipitation, are included among dynamical-downscaling outputs. Most notably for DWR, three-dimensional winds, radiation fluxes (solar and longwave) at the surface, and humidity variables can be outputs from dynamical downscaling. This fuller suite of outputs allows for more complete estimation of evaporation and evapotranspiration (ET) demands and rates. At present, most standard hydrologic models (and all used by DWR) estimate ET rates based on proxy relationships between temperatures and potential ET, relationships fitted to historical observations but that may not remain the same under the changing climate (Milly and Dunne 2011). Notably, these “other” variables, such as winds, humidity and even (to an extent) radiation, are determined by, and have an impact on, conditions in the turbulent layer of atmosphere in the first kilometer (0.6 mile) or so above the surface, the planetary boundary layer. Planetary boundary-layer processes are another facet of local climate (in addition to local land topography) and a natural part of dynamical downscaling that the models used are particularly well suited to address and track as the climate changes. Beyond ET, to model the full range of processes of snow accumulations and snowmelt that will determine the future of snowpack storage and the largest part of water resources in California, incident radiation at the snow surface is a very important input (e.g., for energy-balance snow models) (Ohara and Kavvas 2006). Temperatures play a role, but most of the energy in snowpacks and snowmelt comes from radiation fluxes on the snow surface. In most existing hydrologic models, and all of the models currently used by DWR, temperature fluctuations are also used as a proxy for estimating these radiation fluxes. The proxy relationships used are based (at best) on historical correlations between temperature and radiation that may not remain valid under future climate changes. In the case of ecological studies, a key parameter is stream water temperature. But stream water temperature depends not only on air temperature but also on radiation and wind. Even in convective environments where there is a confluence of forcing factors on smaller scales, such as orographic influence, convection, and sea-breeze, useful high spatio-temporal resolution simulations have been reported (Cheng and Georgakakos 2010).

In all these cases, the dynamical-downscaling approach can provide the desired atmospheric variables, beyond just temperatures and precipitation. Thus, dynamical downscaling will likely provide the most reliable irrigation-water demand estimates (as well as improved snow and stream temperature estimates) for California for the 21st century. Ideally, such downscaling would not be limited to standard atmospheric regional-climate models, but rather would use developing watershed-scale coupled atmospheric-hydrologic hydroclimate models (Kavvas et al. 2013) to best capture local land feedbacks, as well as the more detailed representations of atmospheric conditions.

Dynamical downscaling also provides levels of temporal detail necessary for many focused evaluations that DWR may require. For flood studies to determine dimensions of hydraulic structures, such as dams and levees, and for flood plain management, it is necessary to simulate precipitation and runoff at no longer than hourly intervals. Similarly, for sediment transport, nutrient transport, heavy metal transport, and other environmental studies, it is again necessary to resolve the modeled transport process at no longer than hourly intervals, because the most important transports occur during flood events. The necessary hourly precipitation data for such studies are routinely provided by the dynamical-downscaling approach. For the simulation of fires, it is necessary to simulate fire-transport mechanisms, in addition to temperature, which depend on the three-dimensional wind field (both speed and directions), at spatial resolutions less than or equal to 9 km (6 mi) and at time intervals less than or equal to one hour. Doing so makes it possible to resolve the effect of steep topography of mountainous terrain on the evolution of the wind fields. The dynamical-downscaling approach routinely provides three-dimensional wind field at fine spatial-grid resolution (typically at 3 km (<2 mi) over specified watersheds and at 9 km (5 mi) over specified geographical regions, such as California). In hydropower production studies, it is necessary to resolve the diurnal cycle in energy production to meet the peak demand, which would necessitate hourly precipitation-runoff data, as provided routinely by a dynamical-downscaling approach that utilizes a watershed-scale hydroclimate model (Kavvas et al. 2013).

In practice, however, dynamic models have their own important limitations. First, they use *parameterizations*, simple mathematical rules that represent features (e.g., convective cloud formation) too small to be resolved by the model. These rules have been developed using measurements and/or detailed numerical experiments that could be limited and not valid for all regions or atmospheric conditions, even under the present-day climate (Randall et al. 2003). Like their global dynamic-model counterparts, regional models generally produce solutions that are biased. For this reason, climate impact researchers usually do not use the outputs from dynamic models directly without some form of bias correction (Georgakakos et al. 2012; Maurer et al. 2013; Pierce et al. 2015). However, bias correction, if applied to meteorological fields, may produce meteorological fields no longer physically consistent and likely to re-insert some of the implicit assumptions regarding long-term stationarities that plague statistical-downscaling methods. Thus, the bias corrections frequently required eliminate, at least in part, one of the most important perceived benefits of this technique. Finally, dynamical-model simulations require considerably more computational resources than statistical-downscaling methods. Consequently, the number of processors and the amount of storage required has traditionally limited the length and number of dynamical-downscaled simulations available.

Some promising techniques are becoming available in which the outputs from the GCMs are bias-corrected before they are used as inputs to regional dynamic climate models (Colette et al. 2012; Pryor and Barthelmie 2014; Walton et al. 2014; Guttman et al. 2012). These can also be used with statistical-downscaling approaches (e.g., Maurer et al. 2014; Peleg et al. 2014), whereby global-model outputs used as inputs to the regional models are corrected with reanalysis data before they are used in statistical downscaling. Still, biases are likely to be introduced by imperfections in the regional-model simulations, even when the global-scale fields have been bias-corrected prior to their use as regional-model inputs. Accordingly, even with these hybrid approaches, a final round of bias corrections may be required.

Statistical Downscaling

Key Point 4.3: Statistical downscaling has the advantage that downscaled products are readily available or can be produced for a large number of climate change scenarios from different global models and under a variety of different assumptions. That said, statistical downscaling hinges on the assumption of "stationarity," wherein the model is developed from relationships of historical large-scale to historical finer-scale variations, and depends on the quality of historical observation data used to develop the statistical-downscaling methodology.

Key Point 4.4: Statistical-downscaled products are acceptable to meet immediate needs, as well as for continuity, consistency with efforts by agencies other than DWR, and convenience. Nonetheless, either new statistical methods or, preferably, dynamical downscaling will be needed to address many issues that DWR is likely to face in the future.

To date, two main methods of downscaling have been applied in State of California studies, and both were statistical-downscaling methods. Early on, and as well as in the recent Bay Delta Conservation Plan (BDCP) climate change assessment, downscaling has been accomplished by what is sometimes called the "delta" method. The *delta method* uses observed historical climate variations as its only example of short-term (days to decades), high-resolution climate variability, and simply superposes long-term averaged climate changes computed from the global-model outputs onto the high-resolution historical record. The superposed changes are usually the differences between monthly, seasonal, or annual averages of each climate variable, averaged over decades-long windows typically, for a window of time in the climate-change projection versus a window of the same length in a historical simulation by the same climate model. Temperature differences in degrees Celsius are added to the historical temperature series, and precipitation differences as percentages of the historical means are multiplied onto the historical precipitation series, to create a delta-method downscaled climate-change scenario. In a classic but recent application of the approach, BDCP applied delta-method corrections to the historical record, with the particular "deltas" derived from averages of multiple climate-change projections near various extremes in the range of the ensemble of projections available at the time of their analyses.

Because of its simplicity, and because the delta method guarantees that all of the known climatological (long-term average), small-distance spatial and short-term temporal fluctuations and linkages present in the real world will be preserved in the downscaled climate-change scenarios, this method is the usual starting point. It is the most commonly applied, downscaling strategy in local climate-change impact analyses. By its nature, if done correctly, the delta method easily eliminates average model biases, such that bias correction is not a required separate step. The three primary limitations of the delta method are as follows:

1. It provides no strong basis for assuming that the historical climatological, short-distance, and short-term climate relations within the state will remain unchanged as global climate change takes hold.
2. It offers no reason to believe that the particular sequences of wet years and dry years, and other historical artifacts, will ever be repeated again, and so too much reliance on the delta method may lead to systems "tuned" to details of the historical record of climate variability that will not be seen again.
3. It does not readily allow projected changes in extreme events (especially short-term extremes) to be modified in resulting climate scenarios. Given the great extent to which extreme events — such as droughts, floods, and wet years — are critical to the functioning of California's water systems (Dettinger et al. 2011; Dettinger and Cayan 2014), this significantly limits the robustness of impact estimates employing delta-downscaled scenarios.

In a closely related approach, climate-change experiments with DWR's various water-management models, associated with the California Water Resources Simulation Model (CALSIM), to date have used a strategy that shares important characteristics with the delta method. In the more recent of these experiments, streamflow responses to selected climate change scenarios downscaled by the Bias-Corrected Spatially Disaggregated (BCSD) downscaling method, which is detailed below, have been simulated with a full hydrologic model (the Variable Infiltration Capacity [VIC]) model. Then the resulting long-term average changes in monthly mean streamflows at CALSIM inflow sites have been calculated from the VIC-model outputs. Those changes have been superimposed on the historical record of inflows by using a simple delta-style approach. In no small part, the choice to insert climate change into CALSIM in this way reflects the fact that the historical record of year-to-year inflow variations into major reservoirs is hardwired into the constraints sets of the massive linear-programming optimization problem that CALSIM models solve to produce their results (though that hardwiring can be loosened, as demonstrated by Cloern et al. 2011).Some DWR efforts have explicitly preferred this application of the delta method to the historical inflows, owing to a desire to preserve decadal-scale climate/inflow variations. Those variations have been presumed crucial to the operations of the water systems and are expected to continue largely unchanged into the future. The three limitations of the delta method listed above also apply to the form of delta method that has been used in past CALSIM applications. In particular, more than one tree-ring reconstruction of California's precipitation regime, which uses tree-ring widths, has shown that the decadal climate variations — which some DWR staff would seek to ensure is incorporated into the CALSIM experiments specifically by use of this delta approach — have only been present in California's climate intermittently during the past 350-2000 years (St. George and Ault 2011; Meko et al. 2014). Consequently, using the delta method to ensure that historical copies of this intermittent form of climate variation are present in all CALSIM analyses amounts to a potentially unwarranted assumption that droughts and floods will always occur in sequence and ameliorate each other in precisely the same (historical) sequence, when that outcome is far from certain.

The other method that has been used extensively in DWR studies is the previously mentioned BCSD method (Wood et al. 2004). This method begins by performing a bias correction by determining the percentile rank of each monthly value of a climate variable in the historical record, and separately in a historical simulation by the climate model. It then maps each value from a climate-projection series from its historical-model percentile onto the corresponding observed historical-percentile value. The approach to bias correction "corrects" model outputs across the full range of percentiles instead of correcting only long-term average values (Stoner et al. 2013). In most applications and certainly in the version of BCSD used by DWR, this bias correction step is applied to detrended time series from the climate projections, and then the trend is added back into the corrected series, though this detrending is not always necessary (Dettinger et al. 2004). At this point, a bias-corrected monthly time series at the climate-model resolution has been obtained. The spatial-disaggregation step involves finding a close analogue to each month's values in this bias-corrected version, among the corresponding monthly maps in the historical record. Once a historical analogue has been found, a delta-like correction to the high-resolution records for that analog month is applied to obtain the BCSD-downscaled time series. This method allows new climatic sequences (as simulated by the freely propagating climate model) to be downscaled so that new examples of variability can be explored. Another benefit of this downscaling is that the changes in the character of monthly-or-longer climatic sequencing and variation, which are projected by the climate model in response to changing greenhouse forcings, can be preserved. Recall that the delta method only ensures that long-term (usually decades-long) changes simulated by the models are represented in the downscaled fields. The BCSD method ensures significant levels of bias correction and historically realistic daily-level climate variations (because once an analog month has been identified, the bias-corrected climate-model monthly anomalies are applied uniformly to the daily values that comprise that month's historical weather). The BCSD method has been applied to many dozens of climate change scenarios from dozens of climate models to develop a wealth of 12-km-gridded (7.5-mi) monthly climate scenarios available for many uses (Maurer et al. 2007) and more recently at daily levels (Maurer et al. 2014). The BCSD method, because it manipulates historical daily value fields in a delta-like fashion, does not introduce new forms or historically unprecedented examples of daily-level climate variability (Maurer et al. 2010). Thus, the BCSD method does not provide exploration of new sequences or forms of short-term extremes.

In future applications, DWR may need to use other methods. Some background on other existing and developing statistical-downscaling methods is presented in the next few paragraphs. Other statistical-downscaling methods also exist and have been used in studies by others. Early on, for instance, a variety of “weather generators” were developed by inputting random noise into statistical relations fitted to describe the seasonal and stochastic properties of weather variation at selected stations to synthesize any desired number of more-or-less realistic time sequences of climate variables there. Those weather generators were modified to include changes in means and standard deviations of those inputs to reflect changes identified in climate projections (Wilby et al. 1998) or to reflect changes in weather patterns from climate projections (Hay et al. 1991; Dettinger and Cayan 1992). These weather generators were particularly valued when the number of available climate-change scenarios was very small (because one could turn a single projection into thousands of possible scenarios) and when availability of almost any temporal detail about the short-term fluctuations simulated by the models was nil. Now that literally hundreds of climate-model-projected scenarios are freely available online, use of weather generators for climate-change investigations is much less common. In most instances, the statistical relations used in weather generators (especially for precipitation) are more stochastic than physically informed, so that rather minimal information about changes occurring in the climate models is actually introduced. Indeed, weather generators always struggle to provide truly realistic place-to-place or time-sequence correlations in their generated climate sequences. Nonetheless, various forms of the weather-generator stratagem are possible should DWR ever need very large (thousands-large) ensembles of projections in applications, as in their newly developing explorations of climate change vulnerabilities (i.e., the new “Decision Scaling Study” that has been described to the CCTAG).

In the past few years, several new (albeit closely related) statistical-downscaling methods have come available, which are worth DWR’s consideration for future studies. The close relations among these methods arise from new developments and a lot of interbreeding (of the good variety). To allow daily-scale information from climate change projections to be brought into downscaling results, methods based on a constructed-analogues (CA) strategy (Hidalgo et al. 2008) have in recent years been used to add daily downscaled fields to the previously mentioned, online Maurer et al. (2014) scenarios archive. The CA method identifies combinations of model-resolution historical, daily climate snapshots that best fit the large-scale, model-resolution daily weather outputs from a global climate simulation. It then applies the same combination of fields and multipliers to the corresponding high-resolution historical snapshots, to obtain downscaled daily weather that directly follows the daily weather simulated by a climate model (whether in historical or projection mode). Having developed this new method, a first step was to borrow the bias-correction strategy from BCSD to improve the realism of the resulting downscaled fields (since all climate models yield more-or-less biased outputs); the resulting Bias-Correction Constructed Analogues (BCCA) is a basis for daily fields from Maurer et al. (2010, 2014). A multivariate-adaptive constructed-analogues (MACA) method (Abatzoglou and Brown 2012) came later. The MACA process is perhaps most notable for the fact that, unlike the BCSD and BCCA products and most delta-method studies thus far, climate variables beyond “just” precipitation and temperature — including winds, humidities, and solar radiation — are routinely downscaled (Abatzoglou and Brown 2012) (http://maca.northwestknowledge.net). This offers a statistical alternative to dynamical downscaling, albeit with all the same limitations regarding the questionable implicit assumption that historical statistical relationships between variables and scales will continue to hold under the future climates that all statistical-downscaling methods share and that dynamical downscaling can avoid.

Most recently of all, David Pierce of Scripps Institution of Oceanography and colleagues (Pierce et al. 2014) have overhauled many aspects of BCCA, removing its tendency to smooth over climatic extreme events, its tendencies to miss or even introduce unnecessary biases (Guttman et al. 2014), and its time-scale dependence typical of climate-model biases (Maurer et al. 2013; Pierce et al. 2015). These problems were not widely recognized until the scientific community recently shifted its focus to climatic extremes. The resulting new method, localized constructed analogues (LOCA) (Pierce et al. 2014) is being applied to many historical simulations and projections among the large existing ensemble of Coupled Model Intercomparison Project, phase 5, CMIP5 projections. The resulting fields (at daily, 6- or 12-km [3.7- or 7.5-mile], resolutions for 32 climate models, with two emission scenarios each) will become available for applications (e.g., from DWR by the summer of 2015). Recent developments for LOCA downscaling, and likely other statistical techniques, are aimed at producing downscaled wind and humidity over the California region. This new method appears to offer substantial improvements in historical realism (across a variety of time scales) over previous methods, so it may be worth planning for its availability in future studies.

A growing variety of statistically downscaled scenarios exists or is emerging. Statistical downscaling can be designed to provide downscaled projections at individual stations or on a regular grid. One of the advantages of statistical downscaling to DWR has traditionally been that the delta method can be applied directly to historical data that DWR already has on hand. Also, BCSD outputs (and now outputs from several of the CA-based methods) are freely available online, such that DWR has been able to obtain downscaled fields at will. One of the most recent, complete, and varied of the online archives of statistical-downscaling products can be found at http://gdo-dcp.ucllnl.org/downscaled_cmip_projections/dcpInterface.html (Maurer et al. 2007; Maurer et al. 2014). The archive includes hundreds of scenarios downscaled by multiple methods and even some that have been run through hydrologic models.

Among these and most other widely available statistically downscaled scenarios, results are computed in gridded form. Accomplishing this requires that gridded historical fields at the same spatial and temporal resolutions, as raw materials for the statistical methods, also be available. One consequence of this requirement is that the most widely available statistical-downscaling fields have been gridded at 1/8-degree (roughly 12-km [7.5-mile]) spatial resolutions and monthly or daily temporal resolutions. This is because the most widely used, gridded historical, observationally based, daily temperature and precipitation fields have only been available at those resolutions (Maurer et al. 2002). During the summer of 2014, efforts were made within the statistical-downscaling community to regrid the historical record to 1/16-degree (roughly 6-km [3.7-mile]) daily resolution, and as noted above the newer methods are beginning to be applied to this finer resolution with resulting higher (6-km [3.7-mile]) resolution results. This added resolution may meet some of DWR's technical needs, but where and when even higher resolutions are required, such as in biological or ecological studies, other sources may need to be developed (e.g., even higher-resolution statistically downscaled fields [Flint and Flint 2012] or dynamically downscaled products, as discussed previously). In the pursuit of highly resolved downscaled data, it is always worth considering whether the additional detail from statistically downscaled sources is actually adding new climate information, in addition to assumed parallels between sparse climate data (simulated or observed) and topography. These topographically driven parallels (e.g., temperature or precipitation lapse rates) may or may not be accurate in the future. This is due to unknown changes in physical processes or even in the current world, because in general observations are too sparse to validate these relationships in most of the state's complex terrain. As discussed below, the ability to make this judgment will depend heavily on the health and rigor of our observations and monitoring networks.

These upcoming and existing downscaled products capture monthly-to-daily-scale weather and climate variations and changes. But, as previously discussed, for some important applications higher temporal resolutions will be desirable. Additional methods are available (Cheng et al. 2007; Chow and Levermore 2007; Lee and Jeong 2014) or can be developed to extend statistical-downscaling methods to hourly levels, on demand, with the most difficult limiting factor being (as with spatial resolutions) the availability of historical records representing the "normal" course of those high frequency variations. Long-term historical records of hourly temperatures, precipitation, and other variables are far less common than are daily-level observations (e.g., Higgins et al. 1996). Looking to the future, current technology can easily record and save hourly observation for many variables of interest.

The recent additions to CA downscaling methods have been motivated by recognition of various limitations of the BCSD, delta, and original CA methods; each has learned from the others. Because of this, the products should be getting more realistic in simulating observed climate variability. In most cases, intercomparisons are available as part of developing and documenting the new methods. However, DWR may need to perform some intercomparisons to determine which product is most effective for its purposes. The "best" downscaling for DWR may have requirements that are not among the limitations or tests that have motivated the various developments. In these evaluations, DWR should be open to including not only statistical-downscaling, but also dynamical-downscaling, products as a source of future climate scenarios. This is because all statistical downscaling suffers from the "stationarity assumption" and the need for adequate observational training datasets. In addition, many statistical-downscaling methods are limited to temperature and precipitation fields; when they do produce downscaling of other variables, there may be concerns that historical datasets are not available to establish adequate statistical relationships.

Some Tradeoffs

Key Point 4.5: Both statistical and dynamical downscaling have strengths and weaknesses. The best downscaling approach depends on the specific application for which the downscaled data will be used.

Statistical downscaling is generally valued because (1) statistical methods are computationally efficient and much less demanding that dynamical models, such that many more and longer climate scenarios have been downscaled and are already available online; (2) the methods yield results that are generally unbiased as a matter of course (to extent that depend on how "bias" is defined by each method); and (3) the methods have been simple enough so that a wide range of scientists have implemented, tested, compared, and improved them.

The most damning limitation of the statistical methods, relative to dynamical downscaling (Pierce et al. 2013), is that they are always based on assumptions that relations, some statistics, or some interrelationships between variables or scales identified in the historical period will persist into the nonstationary future despite climate change. If a statistical method applies a lesson from the historical record that no longer applies in the future, then its downscaled products will tend to mislead. For example, if summertime precipitation were to change in the future by way of substantially new sources/processes (e.g., monsoon intrusions or another unlikely source/process), then bias-correcting or bias-constructing analogues from the historical summertime precipitation amounts and patterns might fail in misleading ways that would be difficult to recognize from a purely statistical-downscaling viewpoint. Dynamical models represent physical mechanisms to extent possible (now) and thus are understood to have a much larger likelihood of capturing and properly recognizing such “sea changes” in seasonality and process. Also, as noted earlier, the dynamical approach will be needed if the joint (interacting) impacts of climate change and land-surface changes are to be accommodated in future climate and hydrologic projections.

As suggested, the larger computational burdens associated with dynamical models remain a concern for short-deadline applications, limiting the resolutions, numbers, and lengths of downscaled products that can be generated without allowing time for full-scale deployment and operation of the dynamical models. Dynamical modeling inherently simulates a full suite of climate variables, not at all limited to temperature and precipitation, and does so in physically and internally consistent ways, which no statistically downscaled method accomplishes. To date, statistical-downscaling methods have only been applied in broad applications and archives to produce daily to monthly scale climate variables. As previously noted, dynamical models yield much higher temporal resolutions that will be useful and even necessary for some DWR applications and assessments. Still, regional dynamical model outputs include significant biases, just as do the global models. In some cases, the biases produced by dynamical-model simulations are quite large (Pierce et al. 2013), which must be considered in evaluating the veracity of their (often smaller) projected changes. Thus, for hydrologic and ecologic applications, even dynamically downscaled scenarios require bias correction and mechanistic diagnostics before their results should be readily accepted, much the same as with statistical-downscaling products.

In recent discussions with DWR, it has been stated that dynamical downscaling has been avoided because “sometimes it ends up reversing trends that are indicated in the global-model outputs.” For example, Pierce et al. (2013) found that some regional dynamic models suggest increased monsoonal activity in the southeast part California, in contradiction of the projections from the outputs from regional statistical-downscaling models. Another California-based example of this sort of disagreement is suggested by work in Hughes et al (2012), wherein the large-scale atmospheric water-vapor fluxes described by a global-scale reanalysis fail to capture the more local influences of a barrier jet that often develops west of the Sierra Nevada. The result is a situation where global models describe most vapor flux into the state as exiting to the east, whereas in more detailed representations the vapor exits to the east and sometimes to the north. If the more subtle conditions that determine frequency or intensities of barrier jets change with global warming, broad changes in precipitation patterns within and around California might be implied that would not be represented in the global-model precipitation patterns or statistically downscaled precipitation fields. Instead, those broad chances might be represented in the regional model outputs. The strategy of ignoring dynamical modeling results, if they disagree with the global models, is probably misplaced. If the dynamical models respond to the large-scale, global-model conditions imposed on them with local trends that differ from what the global-model outputs indicate, then two broad causes might be at work: (1) The regional-climate model is in error, or (2) the global model (and probably any statistical-downscaling method applied to the purely global-model outputs) is not capturing some particularly significant aspect of the local climate that depends on the local land forms and surfaces. That is, it is possible that the large-scale meteorological conditions that the regional model is embedded within yield different but more correct outcomes when interacting realistically with the more realistic, high-resolution atmospheric physics and dynamics, and land-ocean topography and surface properties included in the regional model. Thus, rather than assuming the global-model trends are necessarily the more accurate projections, these cases where the regional model reverses or ignores the global-model trends are reasons to pay even more attention to what the regional model is doing. These are cases when it behooves DWR and its partners to investigate trends mechanistically to determine which of the two options above may be more correct.

Summary and Conclusions

Key Point 4.6: DWR should consider designing or supporting an intercomparison of downscaling methods and sources that reflects its particular applications and needs.

This chapter has presented strengths and weaknesses for using statistical and dynamical downscaling to obtain needed future climate outlooks. Ideally, dynamical downscaling should provide physically realistic simulations of the full suite of atmospheric and land surface processes. Statistically downscaled scenarios are already available (or soon will be) by quite a few different approaches for many GCM simulations. To determine which downscaling method or product will give DWR the most reliable results in its planning and adaptation efforts, intercomparisons of the results from several of the methods are probably warranted. Such intercomparisons are being conducted by other agencies or groups (e.g., Pierce et al. 2013; Mearns et al. 2013; Burger et al 2012; Maurer et al. 2010), but there certainly is no single answer to the question, “Which method is best?” There is no single answer because the answer will depend on the application that will be made of the downscaled products. For example, CALSIM II could only accommodate monthly climate fluctuations and changes, whereas other models (e.g., the VIC model) require daily climate inputs. Obviously, the ability of a particular downscaling scheme to accurately represent daily-level weather extremes will be of limited use in CALSIM II applications but may be the crux of some VIC analyses. Different applications will require different variables and scales for their inputs, such that the ability of a downscaling method to capture one variable or scale might be make-or-break in one case and of little relevance in another. DWR may find that its requirements for accuracy are best served by an intercomparison study of its own devising, one tailored to its own particular applications and needs.

Key Point 4.7: All downscaling efforts ultimately draw on, or are justified by, comparisons to real-world observations. Thus, frequent and regular observations of a suite of climate and hydrologic variables at many locations are an enabling factor in downscaling success, whether by statistical or dynamical methods. DWR should develop an appraisal and plan for the readiness of the networks of observations that underpin its climate-change downscaling activities.

Finally, in any discussion of downscaling methods and products, an important — but often neglected — consideration has to be the widespread availability, continued availability, and quality of observations. Downscaled fields do not create new information from whole cloth. The new information they create should only be valued to the extent that it is realistic and might be expected to recapitulate relevant historical conditions or statistics. Downscaled fields that greatly deviate from real-world conditions are likely to yield misleading conclusions. Downscaled versions of historical climate simulations should be compared with observations from the same locations and same periods. If the downscaled conditions greatly deviate from observations, then the downscaled products should be disregarded or somehow corrected. The corrections generally need to be made in ways that can be extended by some justifiable manner to the entirety of the downscaled fields, including to those many places where there are no observations that can provide corrections directly, as well as to the future under a changing global climate. It is important to consider how the downscaling analysts have accommodated these needs in whichever downscaled product is used. Nonetheless, it is important to judge whether the errors identified (e.g., through comparisons to observations) are actually relevant to the application and are large enough to become a problem. As noted earlier, and especially for statistical downscaling, if observations of the variable in question (e.g., temperature, humidity, winds) or time scale (e.g., hourly, daily, monthly) are not available, then it becomes impossible to check the quality of the downscaled products. Some variables, such as wind, radiation, and humidity, are observed more sparsely than precipitation and temperature. In the case of statistical downscaling in the absence of the appropriate observations, it may be difficult even to infer the statistical relations that would make downscaling possible. Resorting to using modeled atmospheric variables (e.g., atmospheric reanalyses) may be necessary, but doing so begs the question of whether the model results are physically realistic. Accordingly, a long view of the climate-change downscaling enterprise should provide motivation for DWR to plan carefully for its future observational needs. In a changing climate, observations — which are the only certainties we will have — will become more valuable, and the need for observations will become more varied, not less so.

Chapter 5. Recommendations for Future Work

Introduction

This chapter presents recommendations for other future improvements to climate change analysis for water resources planning. It first presents a set of additional recommendations for improving climate change analysis in DWR and other large-scale water resources planning. It then presents a second set of recommendations on improving water resources planning under climate change for smaller-scale regional and local water-resources planning programs that are not directly implemented by DWR, but which are strongly influenced by DWR. There is some overlap between the two sets of recommendations.

Recommendations Concerning Climate Change Analysis in Larger-Scale Water Resources Planning

5.1 Screen Viable Water Resources Planning Options.

A first significant recommendation for large-scale water resources planning is for DWR to develop an integrated framework for screening viable water-resources planning options under climatic and water demand change. Those options should then be used to develop adaptive management and planning strategies and to examine what-if scenarios for modifying current operational water-resources management constraints. This section outlines needed attributes of this framework. While this discussion primarily focuses on the State Water Project, DWR should undertake similar efforts throughout the state, in collaboration with other federal, State, and regional water-management agencies.

California’s storage and transmission system modulates the large fluctuations in natural water supply (in the form of rainfall and snowmelt) to meet demands. It provides two-thirds of the state’s drinking water; supports the irrigation of 7 million acres of the world’s most productive farmland; and provides healthy habitat to hundreds of species of fish, birds, and plants. This is currently done on the basis of guide rules estimated from extensive numerical simulations using historical data. For instance, for flood control, the guide rules typically associate reservoir releases with observed precipitation totals for a certain time of year, and in some cases are simply only functions of time of year (independent of observed rainfall) (Willis et al. 2011).The use of weather forecast information for the management of reservoir waters is uncommon. As climatic changes occur and the extremes of the natural water supply begin to change, the guide rules will become less effective in management of water supplies to meet downstream demands while maintaining required levels of flood protection. The result is that screening options for water planning, based on simulations utilizing these guide rules, may lead to excessive water loss or unduly increased flood risk (Yao and Georgakakos 2001; Georgakakos et al. 2012).

Accordingly, it is recommended that DWR simulations for water resources planning incorporate adaptive management scenarios (rather than set-rule scenarios) that consider the system of reservoirs of Northern California (rather than focus on individual reservoirs). The INFORM demonstration project of Northern California (Hydrologic Research Center — Georgia Water Resources Institute 2007, 2014) provides templates for developing adaptive management scenarios and incorporating them in operations. Accurate simulation of the California water storage and transmission system is prerequisite to establishing viable options through simulations of adaptive management.

For planning purposes, it is also important for DWR to incorporate a realistic method for representing operational water management in the simulations with climate forcing. This will allow for more reliable assessments of feasible planning options. For instance, to estimate the impacts of extreme event occurrence and magnitude, it is essential to incorporate realistic simulations of the effects of short- to long-range forecasts and their uncertainty on system management. As climate changes, this may lead to the development of a different approach to the use of traditional guide rules, better enabling individual reservoirs to adapt to the changes in natural water-supply extremes. It may also lead to plans for more effective regional cooperation in multi-objective reservoir planning and management (see Georgakakos et al. 2012 for an example). For example, DWR should reassess reservoir operating rules at least every five years, with due consideration given to coordination among reservoirs.

Any water resources planning or management activity is based on the hydrologic conditions of the studied region/watershed. The information on the hydrologic conditions is supplied by hydrologic models. To perform realistic planning and management of California water resources during the 21st century, it is important to employ fully-physically-based hydrologic models (Kavvas et al. 2004; Chen et al. 2004a, 2004b) whose physical parameters can evolve by and can be estimated objectively from the evolving physical conditions of the future, for the simulation of the future hydrologic conditions.

5.2 Provide Centralized Information and Support for Water Managers and Planners.

DWR, in collaboration with regional and local water managers and planners, should provide centralized information and support for water resources management at the State, regional, and local levels through the development of a quality-controlled clearinghouse of climate change information and supporting activities. Several centralized California climate-change-focused resources already exist, such as the DWR climate change website (http://www.water.ca.gov/climatechange/), which includes the *Climate Change Handbook for Regional Water Planning*; the California Climate Change Portal (http://www.climatechange.ca.gov/); and Cal Adapt (http://cal-adapt.org/). However, these existing resources often lack well-developed information pertinent to water resources management under climate change. Before undertaking the recommendations below, DWR should systematically catalog and analyze existing and developing information sources, and identify gaps. All of these recommendations should be implemented in collaboration with regional and local water managers.

5.2.1 Establish a Database and Information System.

DWR should develop a centralized database and information system to support water management and planning applications under climatic and demand change. DWR should develop effective and efficient dynamic-downscaling approaches and databases to support water planning and management under climatic variability and change, as well as quality-control downscaled products with indicators that quantify model performance. DWR also should make the products more accessible through data-sharing agreements with users. Compiling and updating a centralized database of State, regional, and local examples of "best-practice" climate change analyses done for specific water resources plans and environmental impact reports would further enhance cooperation and efficiency among planners and managers.

5.2.2 Establish Climate Competency and Training Modules to Apply Latest Climate Science.

As the statewide leader in applying climate change science to water resources management, DWR has a responsibility to improve the knowledge base of all water managers in the state with respect to this topic. To start, DWR should support the development of easily accessible tools and information that lay out the basics of climatic change and its expected impacts on water resources throughout the state. In addition, DWR should develop demonstration projects for State, regional, and local managers, emphasizing the development of common definitions, vulnerability indicators, and adaptation strategies. This includes developing platforms for social learning, innovation, and collaboration in water planning under climatic and demand change.

5.2.3 Develop Guidance and Tools for Communicating and Managing Uncertainty in Water Resources Planning and Management.

There is substantial uncertainty in estimating water resources impacts of climatic variability and change, and in the development of planning scenarios at all levels, from State to regional to local. DWR should develop guidance and tools for communicating and managing the uncertainty at these levels to facilitate effective adaptive strategies that incorporate risk, leading to statewide risk-based management and planning.

5.2.4 Establish a Process for Assessing the Strengths, Gaps, and Suitability of Planning and Management Models Relative to Planning and Management Needs.

Several models exist that are used for water resources planning and management, including hydrology models and decision support models. While these models were originally developed for specific purposes, their use is stretched to accommodate planning and management needs arising from hydroclimatic, demand, and socio-economic changes. DWR should develop a consistent process to assess the strengths and applicability of existing models relative to emerging planning and management needs, identify further model improvements, and/or identify synergetic model uses that leverage their collective strengths and mitigate their individual gaps. These models should also be evaluated with respect to their adaptability to the changing hydroclimate conditions. These models' parameters could evolve with the changing hydroclimate conditions. Those models whose parameters can be updated objectively under the changing conditions of the future hydroclimate should be the preferable tools for water resources planning and management.

5.2.5 Continuously Monitor Developments in Climate Science and Methodologies, and Share Results.

Climate change science and technical approaches are evolving rapidly. This report is based on a snapshot of climate science as of early 2015. Led by the Office of the State Climatologist of California, DWR should develop a proactive strategy for obtaining and monitoring the latest developments in climate science and technical approaches, and share results with water resource managers throughout California. Such information sharing might include updates on the latest climate models, improvements in extreme events and downscaling methodologies, and new and/or improved hydrology forecasting tools and models.

5.2.6 Coordinate DWR Climate Change Planning with Other State Agencies, the Southwest Region, and National Activities.

DWR's climate-change planning efforts can inform and be informed by climate science developments at the State, regional (Southwest Region), and national scales. At the State level, the Climate Action Team (CAT) Research Working Group[1] coordinates climate-change research activities. About 20 State agencies from the CAT Research Working Group, including DWR, have developed a Climate Change Research Plan for California to delineate the research that California intends to support in the next five years. This group has also created and continuously updates a catalog of research efforts that California has supported since the early 2000s[2]. The first major implementation of the CAT Research Plan is the preparation of California's Fourth Climate Change Assessment, due in 2018. DWR has and will continue to play a key role in this group to ensure its specific research priorities are taken into account.

At the regional levels, DWR is already directly or indirectly connected to multiple activities, including the Southwest Climate Science Center,[3] which covers six Southwestern states and the California Landscape Conservation Cooperative[4]. DWR also coordinates with the California Nevada Applications Program (CNAP)[5] at the Scripps Institution of Oceanography. DWR should continue to coordinate with these and other regional institutions.

At the national level, the U.S. Global Change Research Program[6] coordinates all climate research activities funded by the federal government. As required by federal law, this entity has coordinated the preparation of National Climate Change Assessments. The White House unveiled the last National Assessment in May 2014. DWR should participate in the effort to help guide the next National Assessment (2018), to produce more actionable science on water issues relevant to California and the Southwest in general.

5.3 Establish Programs to Support Research in Water Resources Planning and Management under Climate Uncertainty and Trends.

Enhancing the effectiveness of water-use planning and management in California with respect to a variety of decisions affected by climate change will require improvements and advances in the methods and data underlying water resources planning and management under climate uncertainties and trends. Those improvements will require directed research. DWR should sponsor or coordinate research and development to (1) improve regional projections of climatic change variables, (2) develop decision-support tools, and (3) develop and evaluate on-the-ground adaptive management approaches capable of encompassing the range of uncertainty and potential extremes in regional projections. Such research and development will allow for stronger risk-based management at local and regional scales. Understanding the linkages and transitions required to move from large-scale to regional to local management of California's water resources will maintain (and may improve) overall water-use effectiveness, and merits additional research.

[1] http://www.climatechange.ca.gov/climate_action_team/research.html
[2] http://cal-adapt.org/research/
[3] http://www.doi.gov//csc/southwest/index.cfm
[4] http://californialcc.org/
[5] http://cnap.ucsd.edu/
[6] http://www.globalchange.gov/

5.4 Develop Guidance and Incentives for Better Monitoring of Climate Change Impacts.

DWR should analyze gaps in monitoring of water resources systems that deter detection of climate change impacts and trends. DWR should then develop guidance and incentives for improved monitoring systems (e.g., additional stream gauge networks) to fill those gaps.

Recommendations Concerning Climate Change Analysis in Regional and Local Water Resources Programs

5.5 Support Collaboration between DWR's Climate Change Program and Regional and Local Water Resources Planning Practitioners.

As mentioned in Chapter 1, there are a number of other planning activities being performed by local or regional resource managers that DWR supports, provides context for, or influences. Table 5-1 shows some of the major planning activities that DWR supports. Additional local planning processes that may incorporate data or analysis provided by DWR include regional and local climate vulnerability analyses and adaptation plans, habitat conservation plans, water-system-specific drought management and emergency response plans, local hazard mitigation plans, local stormwater and flood management plans, county and municipal general plans, and watershed assessments.

Given the highly interlinked and interdependent nature of California's water resources and economic systems, if regional and local water systems cannot effectively adapt to climate change, then the ability of the State's water system as a whole to respond and adapt to climate change will be seriously jeopardized. The inability of regional and local water systems to adapt to climate change will adversely affect DWR's water management in ways that are difficult to foretell.

Table 5-1 Programs Supported by DWR (same as Table 1-4)

Program	Periodicity	Capability/Applicability of Conducting General Climate Change Impacts Analysis	Extreme Conditions Analysis Conducted to Date	Capability/ Applicability of Conducting Extreme Conditions Analysis	Agency
Central Valley Flood Protection Planning	5 years	Limited applicability, flood protection vulnerabilities and impacts are predominantly driven by extreme events.	Pilot study of threshold analysis (flood)	In development	DWR staff under auspices of CVFPB
Urban Water Management Planning	5 years	Limited — this type of analysis is not explicitly required of UWMP.	Worst 3-year drought on record	Varies by local water district	Local water districts
Agricultural Water Management Planning	5 years	Required to “include an analysis, based upon available information, of the effect of climate change on future water supplies” ([Water Code §10826 (c)]). Interpretation of this requirement left to DWR and AWMP groups. Capacity to conduct analysis varies among AWMPs.	No requirement	Varies by local water district	Local agricultural water suppliers
Integrated Regional Water Management Planning	Varies — depends on funding cycles	Required to evaluate "the adaptability to climate change of water management systems in the region." Interpretation of this requirement left to DWR and RWMGs. Capacity to conduct analysis varies among RWMGs.	No requirement	Varies by RWMG	RWMGs
Regional Flood Management Planning	No requirement	Limited — this type of analysis is not a focus of the grant funding.	Rely on existing studies, no new analysis.	Limited — this type of analysis is not a focus of the grant funding.	Regional Flood Management Groups
Groundwater Management Planning	No requirement	Limited — this type of analysis is not required in legislation and not a focus of the grant funding	No requirement	Limited — this type of analysis is not a focus of the grant funding.	Local Groundwater Management Groups

Notes:

AWMP = agricultural water management plan, CVFPB = Central Valley Flood Protection Board, DWR = California Department of Water Resources, RWMG = regional water management group, UWMP = urban water management plan

Local agencies and water planning regions vary greatly in their technical capacities to perform climate change analysis. Some agencies engage consultants and academic research groups to assist with developing, understanding, and using climate change information, such as global climate model (GCM) downscaling. These experts have also been consulted to aid integrated regional water management (IRWM) regions in meeting the IRWM Guidelines climate-change plan standard. That said, many agencies and organizations lack the technical and financial capacity to incorporate climate change risks into their planning and develop location-specific information. In particular, very small water systems in rural areas, and rural and urban economically disadvantaged communities, face challenges in performing climate change analyses.

Previous efforts by DWR and others, such as the *Climate Change Handbook for Regional Water Planning*, have provided some needed guidance on these subjects. Nonetheless, DWR investments in improving regional and local responses to climate change should be greatly increased. For example, DWR should provide high-level technical assistance in developing decision-support systems, which should be well integrated with those of DWR, for effective anticipatory water management at the regional and local levels. These investments will ultimately result in a more stable California water system, as well as more successful statewide water resources management. To accomplish this, DWR should invest in various existing groups — such as the Water Research Foundation (http://www.waterrf.org/knowledge/climatechange/Pages/default.aspx), the Water Utility Climate Alliance (http://www.wucaonline.org/html/), the Bay Area Climate & Energy Resilience Project (http://www.abag.ca.gov/jointpolicy/projects.html#climate), and the Climate Readiness Institute (http://climatereadinessinstitute.org/) — to access and build the capacity of existing professional networks with strong interests in narrowing the gaps between climate research and water management practice.

CCTAG recommends that DWR develop plans and outreach efforts to support local and regional planning agencies in addressing the following questions:

- How can model outputs be used to assess climate risks on water resources? For example:
    - What duration and intensity of drought conditions should communities prepare for?
    - What frequency and intensity of storms, and extent of flooding, should communities prepare for?
    - How will climate change affect groundwater recharge, stream flows, water temperatures, and fisheries?
    - Does the uncertainty in projections warrant re-estimation of safety factors for the development of water infrastructure with a long lifetime?
- What foundational knowledge is critical before applying climate model products? When using climate model products is not appropriate or feasible, what simpler methods can be used to forecast future climate conditions?
- Do projected climatic extremes and associated impacts warrant the examination of institutional issues associated with established guidelines for water managers and with interagency cooperation?
- What are appropriate impact assessment uses for GCMs and regional climate models (RCMs), and how could they best be incorporated into local and regional planning?
- How can an intercomparison of downscaling methods and sources be designed or supported to reflect particular applications and needs?
- How can an appraisal and plan be developed for the readiness of the networks of observations that underpin climate-change downscaling activities?

- What are the most appropriate methods and hydrologic models for converting GCM and downscaled data into hydrologic and water-resources management information relevant to regional and local water resources planning?
- How can regional and local water managers access these models?
- Where can regional and local planners seek help when questions arise in application of these models?
- What forum or processes exist for regional and local water managers to support continuous learning and improvements for keeping up with latest science and with model applications?
- How can adaptation options that are proactive and increase resilience to climate change impacts be identified and assessed?

By supporting lasting collaboration with regional and local water managers and groups, DWR will benefit from the strengthened linkage between climate science and water resources planning practice.

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Appendix A

Water System Description

Climate change impacts on water systems in California must be considered in the context of California's interconnected water systems. Water in California is managed at the federal, State, and local levels. These systems manage over 40,000,000 acre-feet of water per year to serve over 30 million people and irrigate nearly 6 million acres of farmland. Because of California's seasonal and geographical precipitation patterns, large inter-annual precipitation variability, and geographical distribution of population, storage and conveyance of water play a major role in California water management. Several inter-basin water transfer projects have been built in California by the federal government, State government, and local water agencies. These systems capture and store winter precipitation and spring runoff from the Sierra Nevada mountains and convey it through natural river channels, aqueducts, and pipelines to population centers and agricultural areas throughout the state. Hundreds of smaller projects owned and operated by local water agencies and irrigation districts capture, store, and convey water from local streams, rivers, and lakes to customers. Figure A-1 shows the large inter-basin transfer projects throughout California.

Along with California's large inter-basin transfer projects and small local surface water projects, millions of acre-feet of groundwater are also used to meet the water demands of California's nearly 40 million people. Groundwater makes up between 30 and 60 percent of annual water supplies and serves as a critical source of water in dry years when surface water resources are scarce. Groundwater is not comprehensively managed in California. Some basins have been adjudicated and groundwater pumping is restricted, but in non-adjudicated basins property rights essentially entitle the owner to unfettered use of available groundwater. This situation has led to millions of acre-feet of groundwater being overdrafted throughout the state.

It is likely that climate change will affect large inter-basin transfer projects and smaller local projects by changing runoff patterns, increasing evaporative losses, and increasing demand, leading to increased unmet demand for surface water. Groundwater may be affected directly by changes in precipitation patterns or higher evaporation and evapotranspiration, but indirect impacts may be even more severe as water users increase groundwater pumping to meet the increased unmet demand for surface water.

Figure A-1 Map of California's Water Projects

Appendix B

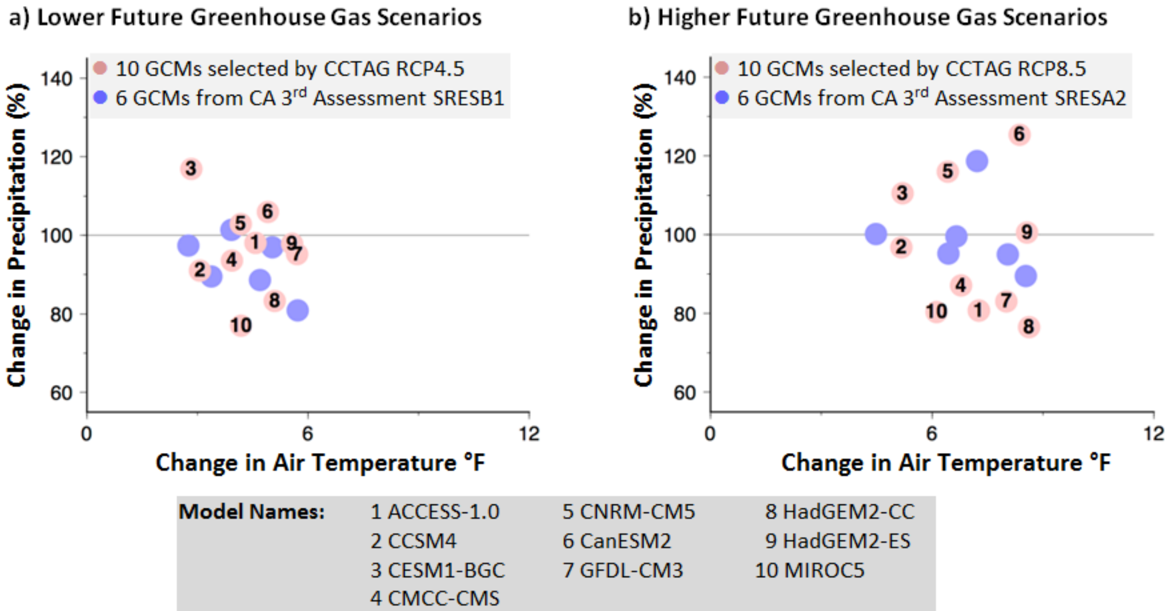
B1: Comparison of the Ten Selected GCMs in this Report with Six GCMs from the California Climate Change Vulnerability and Adaptation Assessment

Global climate models (GCMs) are continuously being developed and improved; however, every seven years the Intergovernmental Panel on Climate Change (IPCC) publishes a new global assessment report. The ensembles of models used in each assessment report have been aggregated by the Couple Model Intercomparison Project (CMIP), and each phase of the CMIP is associated with an IPCC assessment report (AR). (CMIP Phase 3 is associated with AR4, and CMIP Phase 5 is associated with AR5; there is no CMIP Phase 4). Several previous California Climate Change Assessment reports (http://www.climatechange.ca.gov/climate_action_team/reports/index.html) have used six GCMs from the CMIP Phase 3 (CMIP3). The 10 GCMs recommended in this report are from the more recent CMIP5. Because so much research has been done in California by using the CMIP3 models, it is worth comparing this new ensemble of models with the older set of models.

End-of-century changes in air temperature and precipitation, simulated by both sets of models, were compared for the San Diego region (Figure B1-1). Data were not readily available to make the comparison for the Shasta and East of Sacramento regions. Note that between AR4 and AR5, the IPCC changed the greenhouse gas (GHG) emissions scenarios used to force the GCMs. Consequently, there is no way to directly compare models from the two time periods by using the same GHG forcing assumptions. Nonetheless, the GHG emissions scenarios are still similar: CMIP5 RCP 4.5 is similar to SRESB1 from CMIP3 and RCP 8.5 is similar to SRESA2 from CMIP3. In the following comparisons, the 10 recommended CMIP5 GCMs run with RCP 4.5 are compared with the six CMIP3 GCMs used in past California climate-change assessments run with SRESB1. Again, the two models sets are compared with CMIP5 GCMs run with RCP 8.5 and CMIP3 GCMs run with SRESA2. (See Chapter 2 for more information on the RCP and SRES future GHG scenarios.)

From this relatively gross comparison, we conclude that the present selection of GCMs is quite similar to the previous California Climate Change Assessment, in terms of the magnitude and spread of temperature and precipitation change over the 21st century.

Figure B1-1 Model Comparison of End-of-century changes in Air temperature and Precipitation for the San Diego Region



Notes:

CCTAG = Climate Change Technical Advisory Group, GCM = global climate model, RCP = Representative Concentration Pathway (refers to scenarios of future radiative forcings in 2100 of 4.5 Wm^2 and 8.5Wm^2)

Modeled changes in air temperature and precipitation over the San Diego region for 2077-2099, compared with 1961-1990 for the 10 CMIP5 models selected in this CCTAG evaluation, are shown in red. For further comparison, changes for six CMIP3 models employed previously in the 3rd California Climate Change Vulnerability and Adaptation Assessment are shown in blue. For GCM background information and affiliated research institutions, see the CMIP5 Coupled Model Intercomparison Project at http://cmip-pcmdi.llnl.gov/cmip5/availability.html.

B2: Dry and Wet Period Information for Ten GCMs Selected for California Water Resources Planning

For some applications, extreme wet or dry long-term behavior may be a critical element. To this end, an analysis was conducted for each of the 10 selected models for RCP 4.5 and RCP 8.5 to catalogue:

Analysis of the full simulation period of water year (WY) 1851 to WY 2100:

- The longest consecutive set of dry or wet water years.

Analysis of the future projection period of WY 2006 to WY 2100:

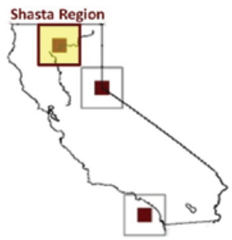
- The driest and wettest 10-year period.
- The driest or wettest water year in that 10-year period.
- The highest 3-day precipitation event (a representation of heavy precipitation events).

These analyses considered water years (October to September) instead of calendar years (January to December) for consistency with California water management practices and fall/winter-dominant precipitation patterns. A dry year is defined as one in which the precipitation is less than or equal to the 25th-percentile precipitation from 50 years of historical simulation (WY 1951 to WY 2000). Similarly, a wet year is defined as one when the precipitation is greater than or equal to the 75th-percentile precipitation of the historical simulation.

Longest Consecutive Stretch of Dry or Wet Years

The entire simulation period, from 1850 to 2100, was examined for each of the 10 selected GCMs for each future GHG scenario (RCP 4.5 and RCP 8.5) to determine the longest stretch of consecutive dry or wet years. GCM-simulated consecutive streaks of dry/wet years that were four years or longer are summarized in Table B2-1. Information on the longest period of dry/wet years for each of the 10 GCMs and three locations is presented in Tables B2-2 through B2-4 for the dry periods and Tables B2-5 through B2-7 for the wet periods. Note that if the longest dry or wet period occurred during the historical period (1850 to present), it means that the model simulated a long dry or wet period during those years. It does not mean that it was actually dry or wet during those years. GCMs try to match historical climate characteristics, not duplicate the actual historical climate pattern.

Table B2-1 Longest Dry/Wet Periods* Simulated by GCMs Selected for California Water Resources Management

Location		Longest Dry Period			Longest Wet Period		
		# Years	Water Years	Model	# Years	Water Years	Model
	Lower GHG RCP 4.5				10	2075---2084	CNRM---CM5
		7	2020---2026	CCSM4	4	1858---1861	CMCC---CMS
		4	1853---1856	CanESM2	4	1952---1955	HadGEM2---ES
		4	1934---1937	MIROC5	4	1981---1985	CESM1---BGC
		4	2046---2049	CESM1---BGC	4	2065---2068	HadGEM2---CC
					4	2083---2086	CanESM2
	Higher GHG RCP 8.5				5	2016---2020	CNRM---CM5
		5	2056---2060	ACCESS---1.0	5	2060---2064	CanESM2
		4	1934---1937	MIROC5	4	1966---1969	HadGEM2---CC
		4	2034---2037	CanESM2	4	1975---1978	CMCC---CMS
					4	1878---1981	HadGEM2---ES
					4	1981---1984	CESM1---BGC
Location		Longest Dry Period			Longest Wet Period		
		# Years	Water Years	Model	# Years	Water Years	Model
	Lower GHG RCP 4.5				8	2077---2084	CNRM---CM5
		6	2021---2026	CCSM4	5	1919---1923	MIROC5
					4	1883---1886	ACCESS---1.0
		5	2008---2012	ACCESS---1.0	4	1889---1892	CMCC---CMS
		4	2012---1015	HadGEM2---CC	4	2050---2053	HadGEM2---ES
		4	2087---2090	CESM1---BGC	4	2066---2069	CanESM2
					4	2066---2069	GFDL---CM3
					4	2076---2079	HadGEM2---CC
	Higher GHG RCP 8.5	4	1893---1896	CESM1---BGC	10	2084---2993	CESM1---BGC
		4	1931---1934	HadGEM2---CC	7	2058---2064	CanESM2
		4	2034---2037	CanESM2	6	2035---2040	HadGEM2---ES
					5	1919---1923	MIROC5
					5	1933---1937	CNRM---CM5
					4	1883---1886	ACCESS---1.0
Location		Longest Dry Period			Longest Wet Period		
		# Years	Water Years	Model	# Years	Water Years	Model
	Lower GHG RCP 4.5				8	1878---1885	ACCESS---1.0
		5	1913---1916	HadGEM2---CC	4	1974---1977	CNRM---CM5
		4	2003---2006	CNRM---CM5	4	2014---2017	HadGEM2---ES
		4	2020---2023	ACCESS---1.0	4	2045---2048	CanESM2
					4	2083---2087	CESM1---BGC
	Higher GHG RCP 8.5				8	1878---1885	ACCESS---1.0
		5	1913---1917	HadGEM2---CC	5	2060---2064	CanESM2
		5	2003---2007	CNRM---CM5	4	1909---1912	CESM1---BGC
		5	2060---2064	HadGEM2---ES	4	1974---1977	CNRM---CM5
					4	2072---2075	HadGEM2---CC

Notes:

GCM = global climate model, GHG = greenhouse gas, RCP = Representative Concentration Pathway (refers to scenarios of future radiative forcings in 2100 of 4.5 Wm^2 and 8.5Wm^2)

This table includes the longest dry or wet spells that are four years or longer. For a complete list of the longest dry and wet periods for the 10 GCMs selected for use in California, see Tables B2-2 through B2-7. For GCM background information and affiliated research institutions, see the CMIP5 Coupled Model Intercomparison Project at http://cmip-pcmdi.llnl.gov/cmip5/availability.html.

Driest/Wettest 10-Year Future Periods

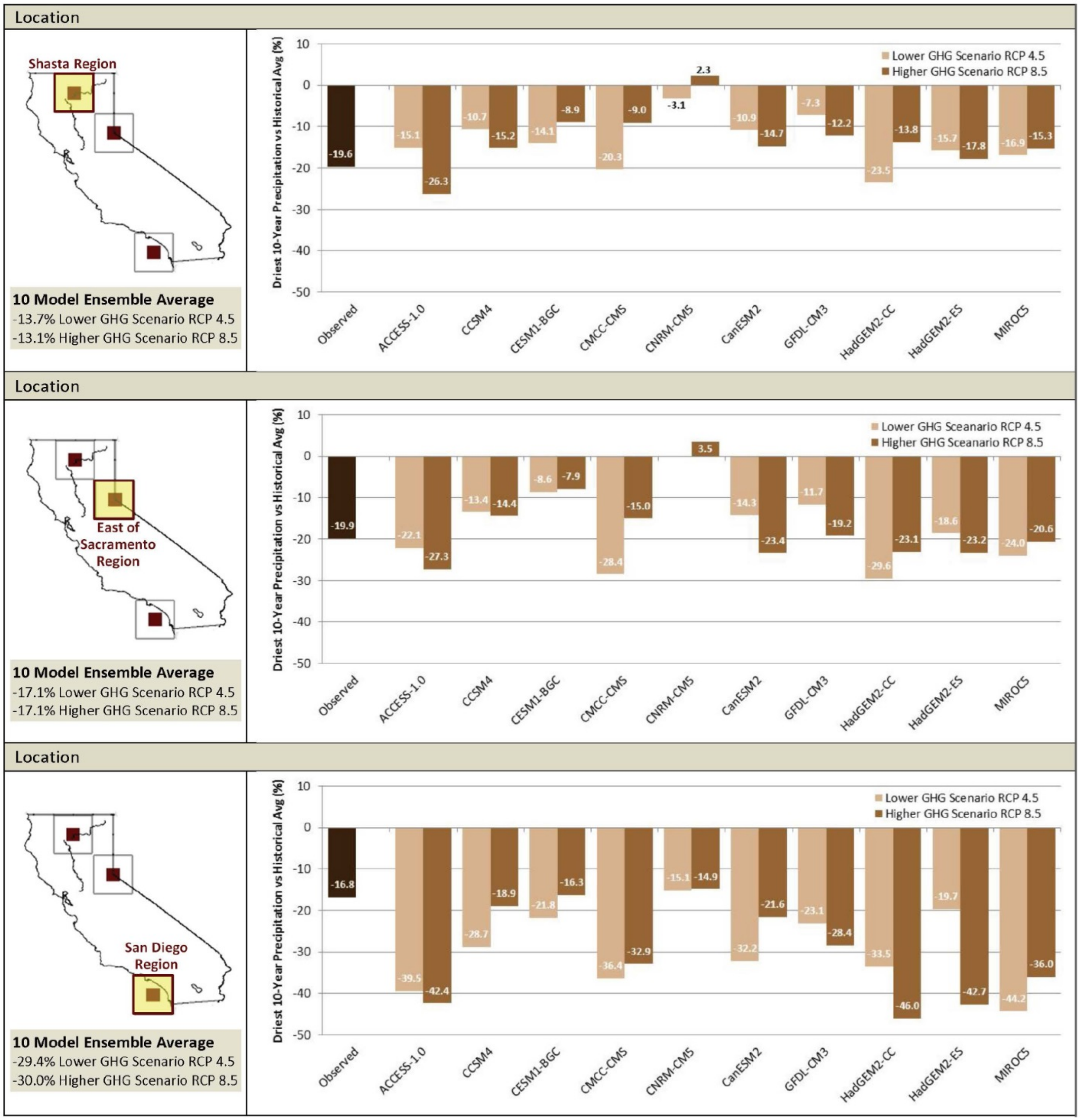
Future precipitation projections for each GCM were examined to identify the driest and wettest 10-year periods for WYs 2007 through 2100 (94 years) for each of the future GHG scenarios (RCP 4.5 and RCP8.5). Water-year precipitation totals were determined from summing the daily precipitation values for that water year. Precipitation totals for sliding 10-year periods were then determined starting with WY2007-2016 and ending with WY2091-2100, a total of 85 10-year periods. The driest 10-year period is the one with the lowest precipitation, and the wettest 10-year period is the one with the highest precipitation.

The driest and wettest 10-year period total precipitation was compared with the average historical simulated precipitation (WY1951-WY2000) (Figures B2-1 [dry] and B2-2 [wet]). For reference, observed California Climate Division data (Vose et al. 2014) were also analyzed to determine the historical observed change in precipitation from the driest or wettest 10-year period compared with the observed historical average. The driest (or wettest) year within the driest 10-year period is also listed. Three locations are shown (Shasta, East of Sacramento, and San Diego) to provide a sense of spatial variability. Ensemble averages are also provided for each location and future GHG scenario. For both the driest and wettest 10-year periods, the largest changes compared with historical averages occurred in the San Diego region.

Details for the driest 10-year period simulated by the 10 selected GCMS are presented in Tables B2-2 through B2-4. Similarly details for the wettest 10-year period are presented in Tables B2-5 through B2-7. The first year of the dry/wet period is in the second column of the table. The number of years in that 10-year period that were classified as dry (below the 25th percentile for annual precipitation) or wet (above the 75th percentile for annual precipitation) is in the third column. The driest/wettest year of the 10-year period is in the fourth column. The driest-year percentage of historical precipitation ([dry water-year value/historical average] x 100.0) or wettest-year percentage of historical precipitation ([wet water-year value/historical average] x 100.0) is shown in the fifth column. The 10-year period average water year precipitation, as a percentage of the historical average water-year precipitation, is shown in the sixth column. (Note that the values for change shown in Figures B2-1 and B2-2 were computed by subtracting the values from column six from 100. For example, in Table B2-2a, the driest 10-year total precipitation for ACCESS-1.0 RCP 4.5 is 84.9 percent of the historical period average, and the corresponding bar in the Figure B2-1 shows 15.1 percent below average. Similarly, in Table B2-5a, the wettest 10-year total precipitation for ACCESS-1.0 RCP 4.5 is 114.4 percent of the historical period average, and the corresponding bar in the Figure B2-2 shows 14.4 percent above average.) The last two columns of the tables look at the full simulated time series of water year precipitation from the historical period (starting in 1850) through the scenario period (2099). The number of years in the longest consecutive dry/wet period is shown in the seventh column and the year that dry/wet period begins is shown in the eighth column. If there are several sequences of the same length, the latter sequence’s beginning year is noted.

The driest and wettest 10-year periods for each model are shown on a timeline in Figure B2-3 (driest periods) and B2-4 (wettest periods).

Figure B2-1 Driest Future Projected 10-Year Periods Compared with Historical Period Averages for Ten GCMs

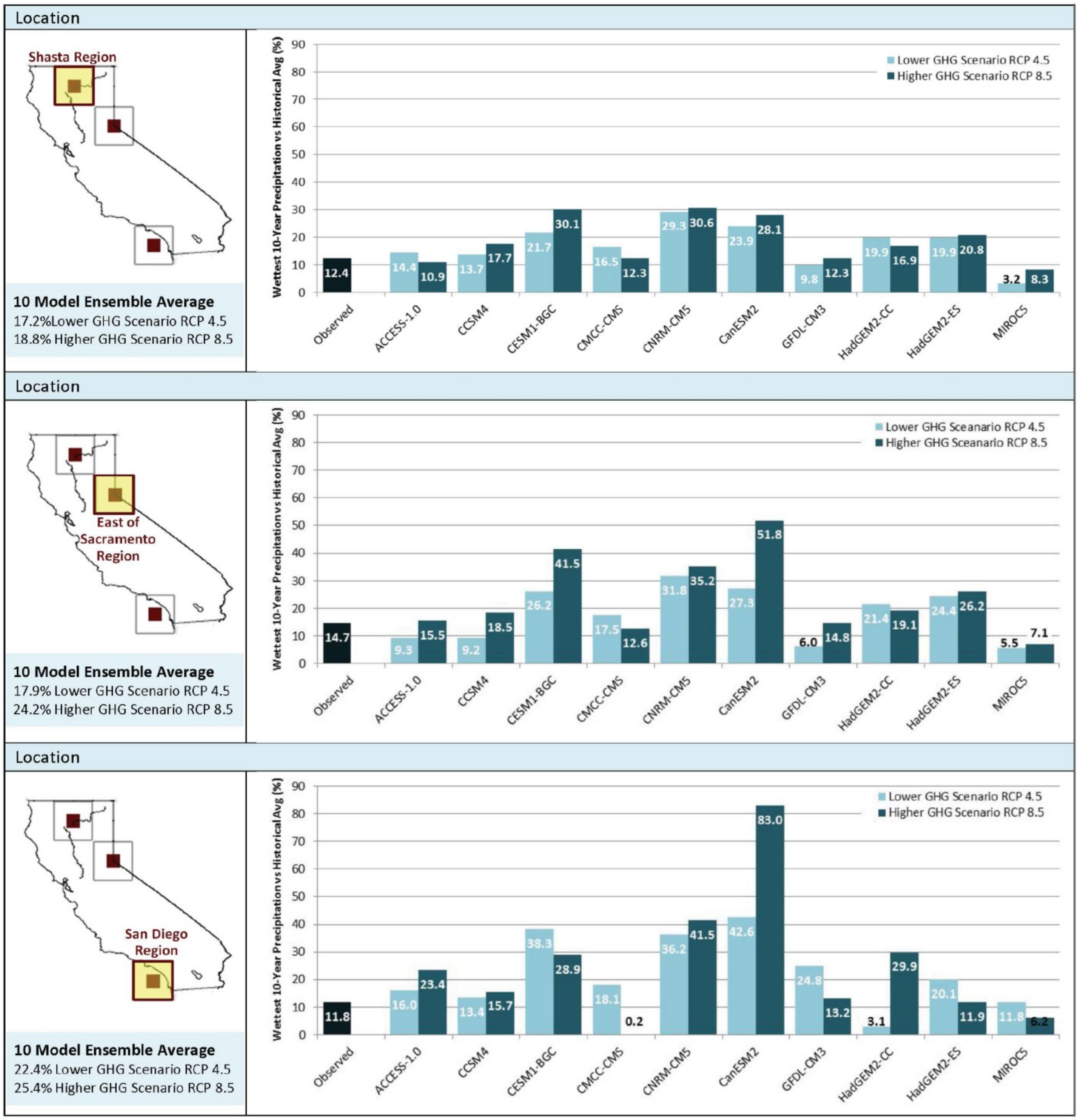


Notes:

GCM = global climate model, GHG = greenhouse gas, RCP = Representative Concentration Pathway (refers to scenarios of future radiative forcings in 2100 of 4.5 Wm^2 and 8.5Wm^2)

Observed data are California Climate Division 1 (Shasta), Division 2 (East of Sacramento), and Division 6 (San Diego). See Tables B2-2 through B2-4 for further details. For GCM background information and affiliated research institutions, see the CMIP5 Coupled Model Intercomparison Project at http://cmip-pcmdi.llnl.gov/cmip5/availability.html.

Figure B2-2 Wettest Future Projected 10-Year Periods Compared with Historical Period Averages for Ten GCMs



Notes:

GCM = global climate model, GHG = greenhouse gas, RCP=Representative Concentration Pathway (refers to scenarios of future radiative forcings in 2100 of 4.5 Wm^2 and 8.5Wm^2)

Observed data are California Climate Division 1 (Shasta), Division 2 (East of Sacramento), and Division 6 (San Diego). See Tables B2-5 through B2-7 for more details. For GCM background information and affiliated research institutions, see the CMIP5 Coupled Model Intercomparison Project at http://cmip-pcmdi.llnl.gov/cmip5/availability.html.

Table B2-2a Driest Periods Simulated by Ten Selected GCMs for the Shasta Region for RCP4.5

Model Name	WY2006-WY2100					WY1851-WY2100	
	Dry 10-Year Period Start	# of Years	Driest Year	Driest Year % of Hist. Avg.	10-Year Period WY % of Hist. Avg.	Longest Run of Dry Years	Year Dry Run Begins
ACCESS-1.0	2084	4	2088	58.41	84.92	3	2088
CCSM4	2020	7	2023	70.24	89.35	7	2020
CESM1-BGC	2040	6	2047	68.82	85.93	4	2046
CMCC-CMS	2051	5	2059	53.24	79.72	2	2059
CNRM-CM5	2008	3	2010	79.14	96.89	3	1930
CanESM2	2018	5	2023	56.01	89.14	4	1800
GFDL-CM3	2023	4	2024	72.97	92.74	3	1976
HadGEM2-CC	2009	7	2018	58.76	76.50	3	2044
HadGEM2-ES	2078	5	2086	52.89	84.26	2	2085
MIROC5	2074	3	2083	52.83	83.10	4	1934
Observed: CA climate division 1	1927	3	1930	56.83	80.38	3	1990

Notes:

GCM = global climate model, WY = water year

Water year historical averages are for WY1961-WY1990. For GCM background information and affiliated research institutions, see the CMIP5 Coupled Model Intercomparison Project at http://cmip-pcmdi.llnl.gov/cmip5/availability.html.

Table B2-2b Driest Periods Simulated by Ten Selected GCMs for the Shasta Region for RCP8.5

Model Name	WY2006-WY2100					WY1851-WY2100	
	Dry 10-Year Period Start	# of Years	Driest Year	Driest Year % of Hist. Avg.	10-Year Period WY % of Hist. Avg.	Longest Run of Dry Years	Year Dry Run Begins
ACCESS-1.0	2056	8	2064	61.98	73.69	5	2056
CCSM4	2013	5	2013	45.47	84.78	3	2067
CESM1-BGC	2067	4	2067	59.05	91.07	3	1935
CMCC-CMS	2066	4	2067	53.22	91.01	2	2073
CNRM-CM5	2021	1	2021	75.02	102.25	3	1930
CanESM2	2034	6	2035	52.30	85.26	4	2034
GFDL-CM3	2014	4	2015	59.03	87.82	3	1976
HadGEM2-CC	2079	5	2085	54.32	86.21	3	2088
HadGEM2-ES	2062	5	2069	51.64	82.25	3	2053
MIROC5	2016	5	2017	52.72	84.70	4	1934
Observed: CA climate division 1	1927	3	1930	56.83	80.38	3	1990

Notes:

GCM = global climate model, WY = water year

Water year historical averages are for WY1961-WY1990. For GCM background information and affiliated research institutions, see the CMIP5 Coupled Model Intercomparison Project at http://cmip-pcmdi.llnl.gov/cmip5/availability.html.

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Table B2-3a Driest Periods Simulated by Ten Selected GCMs for the East of Sacramento Region for RCP4.5

Model Name	WY2006-WY2100					WY1851-WY2100	
	Dry 10-Year Period Start	# of Years	Driest Year	Driest Year % of Hist. Avg.	10-Year Period WY % of Hist. Avg.	Longest Run of Dry Years	Year Dry Run Begins
ACCESS-1.0	2020	5	2020	48.99	77.92	5	2008
CCSM4	2019	6	2023	63.78	86.56	6	2021
CESM1-BGC	2065	5	2066	48.14	91.38	4	2087
CMCC-CMS	2051	6	2051	42.11	71.57	2	2054
CNRM-CM5	2007	2	2012	83.12	99.97	3	1999
CanESM2	2089	5	2092	40.62	85.74	3	2001
GFDL-CM3	2080	3	2081	56.67	88.30	3	1976
HadGEM2-CC	2009	8	2009	34.23	70.44	4	2012
HadGEM2-ES	2078	4	2086	53.40	81.43	3	2085
MIROC5	2074	5	2076	52.53	76.02	3	1962
Observed: CA climate division 2	1923	4	1923	40.60	80.13	2	1990

Notes:

GCM = global climate model, WY = water year

Water year historical averages are for WY1961-WY1990. For GCM background information and affiliated research institutions, see the CMIP5 Coupled Model Intercomparison Project at http://cmip-pcmdi.llnl.gov/cmip5/availability.html.

Table B2-3b Driest Periods Simulated by Ten Selected GCMs for the East of Sacramento Region for RCP8.5

	WY2006-WY2100					WY1851-WY2100	
Model Name	Dry 10-Year Period Start	# of Years	Driest Year	Driest Year % of Hist. Avg.	10-Year Period WY % of Hist. Avg.	Longest Run of Dry Years	Year Dry Run Begins
ACCESS-1.0	2056	6	2056	48.58	72.73	3	2070
CCSM4	2012	4	2013	48.58	85.56	3	2067
CESM1-BGC	2046	4	2049	63.94	92.09	4	1893
CMCC-CMS	2011	2	2017	62.33	85.03	2	2007
CNRM-CM5	2021	1	2021	75.61	103.49	3	1999
CanESM2	2034	6	2034	41.61	76.63	4	2034
GFDL-CM3	2014	4	2015	42.10	80.80	3	1976
HadGEM2-CC	2077	6	2085	38.55	76.93	4	1931
HadGEM2-ES	2060	5	2063	50.58	76.77	2	2062
MIROC5	2049	6	2049	64.90	79.37	3	2049
Observed: CA climate division 2	1923	4	1923	40.60	80.13	2	1990

Notes:

GCM = global climate model, WY = water year

Water year historical averages are for WY1961-WY1990. For GCM background information and affiliated research institutions, see the CMIP5 Coupled Model Intercomparison Project at http://cmip-pcmdi.llnl.gov/cmip5/availability.html.

Table B2-4a Driest Periods Simulated by Ten Selected GCMs for the San Diego Region for RCP4.5

Model Name	WY2006-WY2100					WY1851-WY2100	
	Dry 10-Year Period Start	# of Years	Driest Year	Driest Year % of Hist. Avg.	10-Year Period WY % of Hist. Avg.	Longest Run of Dry Years	Year Dry Run Begins
ACCESS-1.0	2020	7	2020	32.92	60.55	4	2020
CCSM4	2063	5	2069	40.04	71.26	3	2064
CESM1-BGC	2045	5	2045	49.75	78.24	4	2087
CMCC-CMS	2054	5	2054	38.97	63.61	3	2076
CNRM-CM5	2062	3	2068	42.70	84.94	4	2003
CanESM2	2089	5	2091	29.20	67.82	3	2012
GFDL-CM3	2080	4	2088	38.37	76.95	3	1994
HadGEM2-CC	2011	5	2019	28.51	66.50	5	1913
HadGEM2-ES	2021	4	2027	18.40	80.33	3	2057
MIROC5	2074	6	2081	24.38	55.78	3	2091
Observed: CA climate division 6	1958	2	1960	44.17	83.17	2	1989

Notes:

GCM = global climate model, WY = water year

Water year historical averages are for WY1961-WY1990. For GCM background information and affiliated research institutions, see the CMIP5 Coupled Model Intercomparison Project at http://cmip-pcmdi.llnl.gov/cmip5/availability.html.

Table B2-4b Driest Periods Simulated by Ten Selected GCMs for the San Diego Region for RCP8.5

Model Name	WY2006-WY2100					WY1851-WY2100	
	Dry 10-Year Period Start	# of Years	Driest Year	Driest Year % of Hist. Avg.	10-Year Period WY % of Hist. Avg.	Longest Run of Dry Years	Year Dry Run Begins
ACCESS-1.0	2070	6	2072	16.74	57.62	3	2087
CCSM4	2089	3	2095	22.01	81.08	3	2067
CESM1-BGC	2051	3	2059	25.19	83.71	3	2088
CMCC-CMS	2062	4	2067	25.27	67.14	3	2033
CNRM-CM5	2045	2	2054	31.16	85.14	5	2003
CanESM2	2035	4	2043	23.38	78.39	3	1930
GFDL-CM3	2085	4	2092	15.90	71.60	3	2054
HadGEM2-CC	2078	8	2086	23.51	53.99	5	1913
HadGEM2-ES	2060	8	2067	37.80	57.33	5	2060
MIROC5	2061	5	2062	22.14	64.04	3	2061
Observed: CA climate division 6	1958	2	1960	44.17	83.17	2	1989

Notes:

GCM = global climate model, WY = water year

Water year historical averages are for WY1961-WY1990. For GCM background information and affiliated research institutions, see the CMIP5 Coupled Model Intercomparison Project at http://cmip-pcmdi.llnl.gov/cmip5/availability.html.

Table B2-5a Wettest Periods Simulated by Ten Selected GCMs for the Shasta Region for RCP4.5

Model Name	WY2006-WY2100					WY1851-WY2100	
	Wet 10-Year Period Start	# of Years	Wettest Year	Wettest Year % of Hist. Avg.	Decade WY % of Hist. Avg.	Longest Run of Wet Years	Year Wet Run Begins
ACCESS-1.0	2072	5	2075	137.35	114.44	3	1884
CCSM4	2090	6	2095	141.81	113.74	3	2017
CESM1-BGC	2077	7	2082	161.60	121.73	4	1981
CMCC-CMS	2089	6	2098	163.53	116.49	4	1858
CNRM-CM5	2075	10	2077	146.67	129.30	10	2075
CanESM2	2059	7	2067	152.51	123.92	4	2083
GFDL-CM3	2007	3	2010	133.58	109.76	3	2062
HadGEM2-CC	2053	6	2057	176.48	119.85	4	2065
HadGEM2-ES	2011	4	2017	147.93	119.87	4	1952
MIROC5	2059	3	2059	143.23	103.22	3	1889
Observed: CA climate division 1	1899	4	1903	155.69	112.37	4	1995

Notes:

GCM = global climate model, WY = water year

Water year historical averages are for WY1961-WY1990. For GCM background information and affiliated research institutions, see the CMIP5 Coupled Model Intercomparison Project at http://cmip-pcmdi.llnl.gov/cmip5/availability.html.

Table B2-5b Wettest Periods Simulated by Ten Selected GCMs for the Shasta Region for RCP8.5

Model Name	WY2006-WY2100					WY1851-WY2100	
	Wet 10-Year Period Start	# of Years	Wettest Year	Wettest Year % of Hist. Avg.	Decade WY % of Hist. Avg.	Longest Run of Wet Years	Year Wet Run Begins
ACCESS-1.0	2023	3	2024	145.23	110.93	3	1954
CCSM4	2037	5	2046	159.95	117.70	3	1961
CESM1-BGC	2084	6	2085	168.73	130.10	4	1981
CMCC-CMS	2080	7	2089	137.50	112.29	4	1975
CNRM-CM5	2086	7	2091	156.07	130.61	5	2016
CanESM2	2082	7	2084	184.52	128.11	5	2060
GFDL-CM3	2061	5	2068	136.71	112.26	3	1967
HadGEM2-CC	2045	6	2047	161.70	116.90	4	1966
HadGEM2-ES	2033	4	2036	176.92	120.77	4	1978
MIROC5	2071	6	2076	139.77	108.32	3	1975
Observed: CA climate division 1	1899	4	1903	155,69	112.37	4	1995

Notes:

GCM = global climate model, WY = water year

Water year historical averages are for WY1961-WY1990. For GCM background information and affiliated research institutions, see the CMIP5 Coupled Model Intercomparison Project at http://cmip-pcmdi.llnl.gov/cmip5/availability.html.

Table B2-6a Wettest Periods Simulated by Ten Selected GCMs for the East of Sacramento Region for RCP4.5

Model Name	WY2006-WY2100					WY1851-WY2100	
	Wet 10-Year Period Start	# of Years	Wettest Year	Wettest Year % of Hist. Avg.	Decade WY % of Hist. Avg.	Longest Run of Wet Years	Year Wet Run Begins
ACCESS-1.0	2072	4	2075	154.65	109.27	4	1883
CCSM4	2076	4	2077	141.70	109.19	3	2007
CESM1-BGC	2077	7	2078	158.96	126.20	4	1889
CMCC-CMS	2089	3	2098	188.24	117.53	3	1975
CNRM-CM5	2030	8	2036	166.14	131.84	8	2077
CanESM2	2077	6	2086	194.76	127.29	4	2066
GFDL-CM3	2090	4	2096	132.83	106.03	4	2066
HadGEM2-CC	2070	6	2079	173.23	121.39	4	2076
HadGEM2-ES	2011	5	2017	161.30	124.43	4	2050
MIROC5	2024	4	2033	142.73	105.51	5	1919
Observed: CA climate division 2	1899	4	1903	148.93	114.71	4	1995

Notes:

GCM = global climate model, WY = water year

Water year historical averages are for WY1961-WY1990. For GCM background information and affiliated research institutions, see the CMIP5 Coupled Model Intercomparison Project at http://cmip-pcmdi.llnl.gov/cmip5/availability.html.

Table B2-6b Wettest Periods Simulated by Ten Selected GCMs for the East of Sacramento Region for RCP8.5

Model Name	WY2006-WY2100					WY1851-WY2100	
	Wet 10-Year Period Start	# of Years	Wettest Year	Wettest Year % of Hist. Avg.	Decade WY % of Hist. Avg.	Longest Run of Wet Years	Year Wet Run Begins
ACCESS-1.0	2022	5	2024	154.40	115.45	4	1883
CCSM4	2084	5	2088	176.38	118.49	3	2077
CESM1-BGC	2084	10	2085	182.09	141.52	10	2084
CMCC-CMS	2021	4	2021	169.04	112.60	3	1975
CNRM-CM5	2086	8	2087	180.19	135.15	5	1933
CanESM2	2082	8	2089	202.00	151.83	7	2058
GFDL-CM3	2059	5	2068	142.16	114.78	3	1874
HadGEM2-CC	2045	6	2049	150.25	119.12	3	1969
HadGEM2-ES	2033	7	2036	204.28	126.18	6	2035
MIROC5	2071	5	2071	153.87	107.13	5	1919
Observed: CA climate division 2	1899	4	1903	148.93	114.71	4	1995

Notes:

GCM = global climate model, WY = water year

Water year historical averages are for WY1961-WY1990. For GCM background information and affiliated research institutions, see the CMIP5 Coupled Model Intercomparison Project at http://cmip-pcmdi.llnl.gov/cmip5/availability.html.

Table B2-7a Wettest Periods Simulated by Ten Selected GCMs for the San Diego Region for RCP4.5

Model Name	WY2006-WY2100					WY1851-WY2100	
	Wet 10-Year Period Start	# of Years	Wettest Year	Wettest Year % of Hist. Avg.	Decade WY % of Hist. Avg.	Longest Run of Wet Years	Year Wet Run Begins
ACCESS-1.0	2066	5	2075	190.71	116.02	8	1878
CCSM4	2039	3	2039	299.11	113.44	2	2041
CESM1-BGC	2055	5	2064	247.67	138.28	4	2083
CMCC-CMS	2086	4	2089	211.67	118.05	3	2034
CNRM-CM5	2042	6	2044	235.45	136.22	4	1974
CanESM2	2079	3	2080	378.20	142.64	4	2045
GFDL-CM3	2025	5	2033	188.81	124.84	3	1997
HadGEM2-CC	2051	3	2058	163.55	103.06	3	1886
HadGEM2-ES	2042	3	2042	209.61	120.06	4	2014
MIROC5	2008	4	2010	172.39	111.84	3	1906
Observed: CA climate division 6	1934	5	1940	222.07	129.00	3	1978

Notes:

GCM = global climate model, WY = water year

Water year historical averages are for WY1961-WY1990. For GCM background information and affiliated research institutions, see the CMIP5 Coupled Model Intercomparison Project at http://cmip-pcmdi.llnl.gov/cmip5/availability.html.

Table B2-7b Wettest Periods Simulated by Ten Selected GCMs for the San Diego Region for RCP8.5

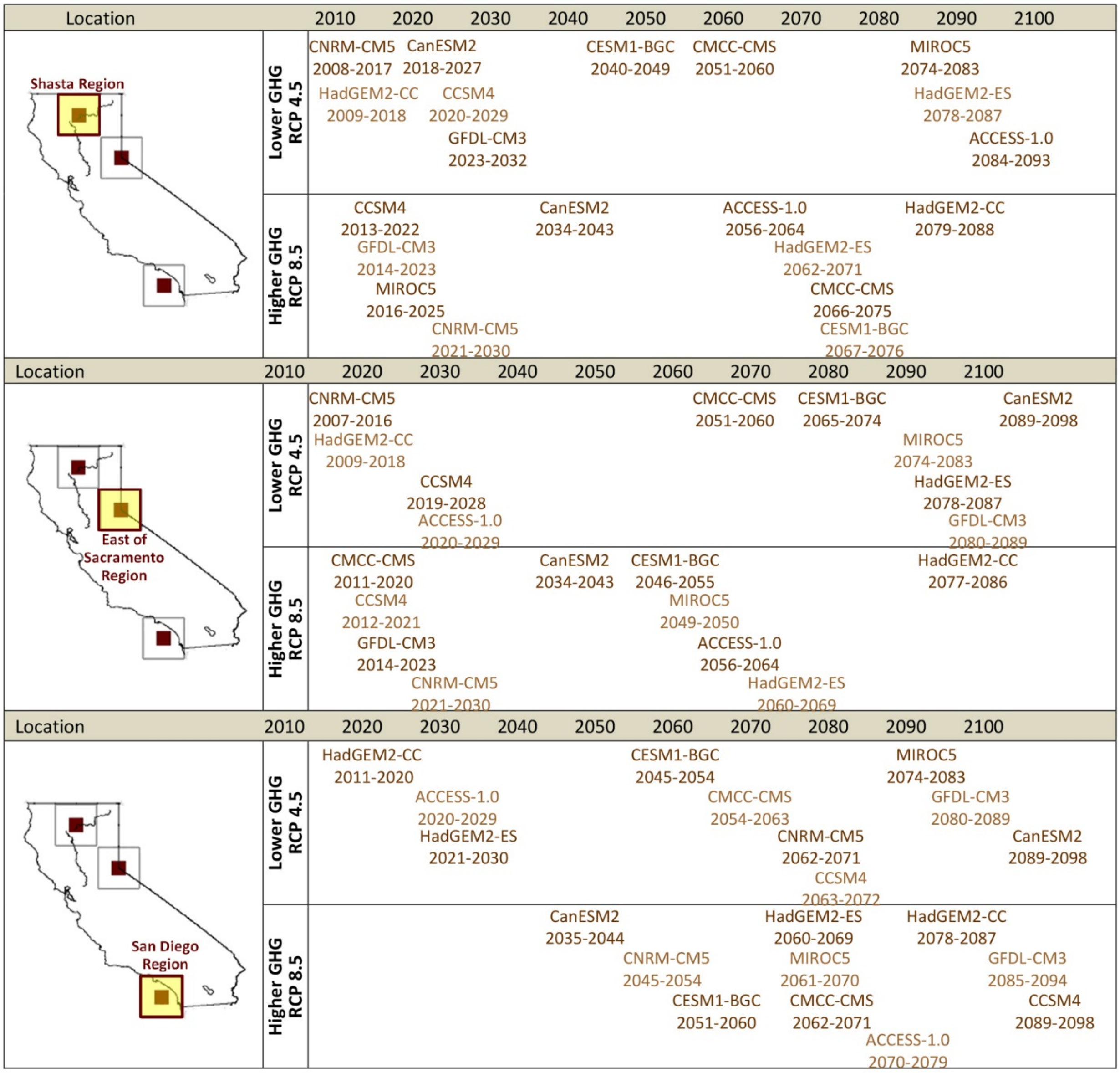
Model Name	WY2006-WY2100					WY1851-WY2100	
	Wet 10-Year Period Start	# of Years	Wettest Year	Wettest Year % of Hist. Avg.	Decade WY % of Hist. Avg.	Longest Run of Wet Years	Year Wet Run Begins
ACCESS-1.0	2018	4	2026	202.10	123.40	8	1878
CCSM4	2070	4	2070	174.22	115.65	2	1993
CESM1-BGC	2031	4	2031	244.71	128.91	4	1909
CMCC-CMS	2069	3	2075	157.73	100.16	3	1975
CNRM-CM5	2086	7	2087	224.74	141.49	4	1974
CanESM2	2082	7	2083	331.77	183.01	5	2060
GFDL-CM3	2058	4	2067	200.27	113.23	3	1997
HadGEM2-CC	2057	5	2064	225.73	129.87	4	2072
HadGEM2-ES	2009	5	2011	152.44	111.86	3	1997
MIROC5	2025	2	2029	225.49	106.21	3	1985
Observed: CA climate division 6	1934	5	1940	222.07	129.00	3	1978

Notes:

GCM = global climate model, WY = water year

Water year historical averages are for WY1961-WY1990. For GCM background information and affiliated research institutions, see the CMIP5 Coupled Model Intercomparison Project at http://cmip-pcmdi.llnl.gov/cmip5/availability.html.

Figure B2-3 Summary of Driest 10-Year Periods Simulated by Ten GCMs Selected for California Water Resources Planning

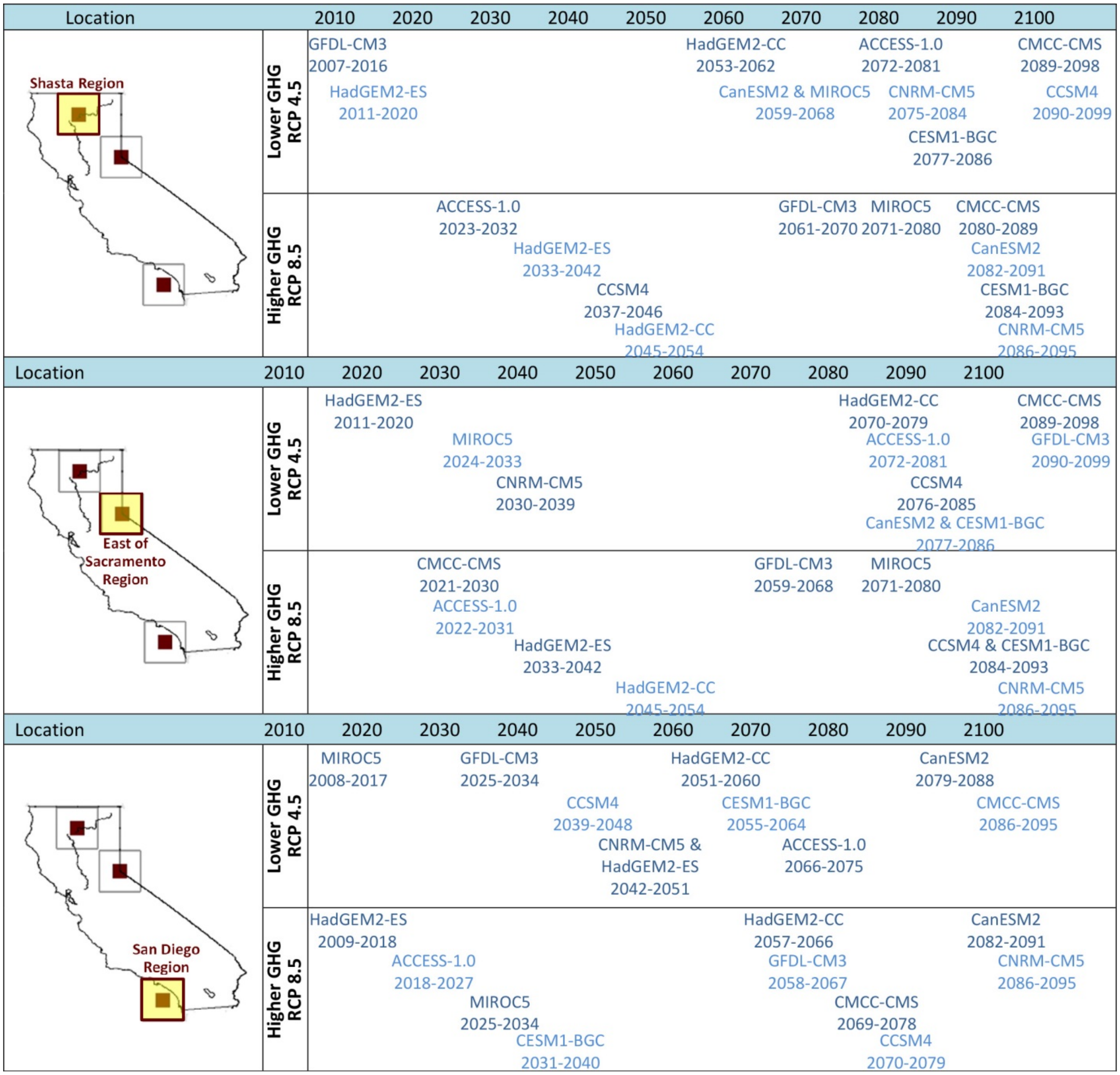


Notes:

GCM = global climate model, GHG=greenhouse gas, RCP=Representative Concentration Pathway (refers to scenarios of future radiative forcings in 2100 of 4.5 Wm^2 and 8.5Wm^2)

For a complete list of properties of the driest decades (driest year, number of dry years during the decade, comparison with historical conditions) for the 10 GCMs selected for use in California, see Tables B2-2 through B2-4. For GCM background information and affiliated research institutions, see the CMIP5 Coupled Model Intercomparison Project at http://cmip-pcmdi.llnl.gov/cmip5/availability.html.

Figure B2-4 Summary of Wettest 10-Year Periods Simulated by Ten GCMs Selected for California Water Resources Planning



Notes:

GCM = global climate model, GHG = greenhouse gas, RCP = Representative Concentration Pathway (refers to scenarios of future radiative forcings in 2100 of 4.5 Wm^2 and 8.5Wm^2)

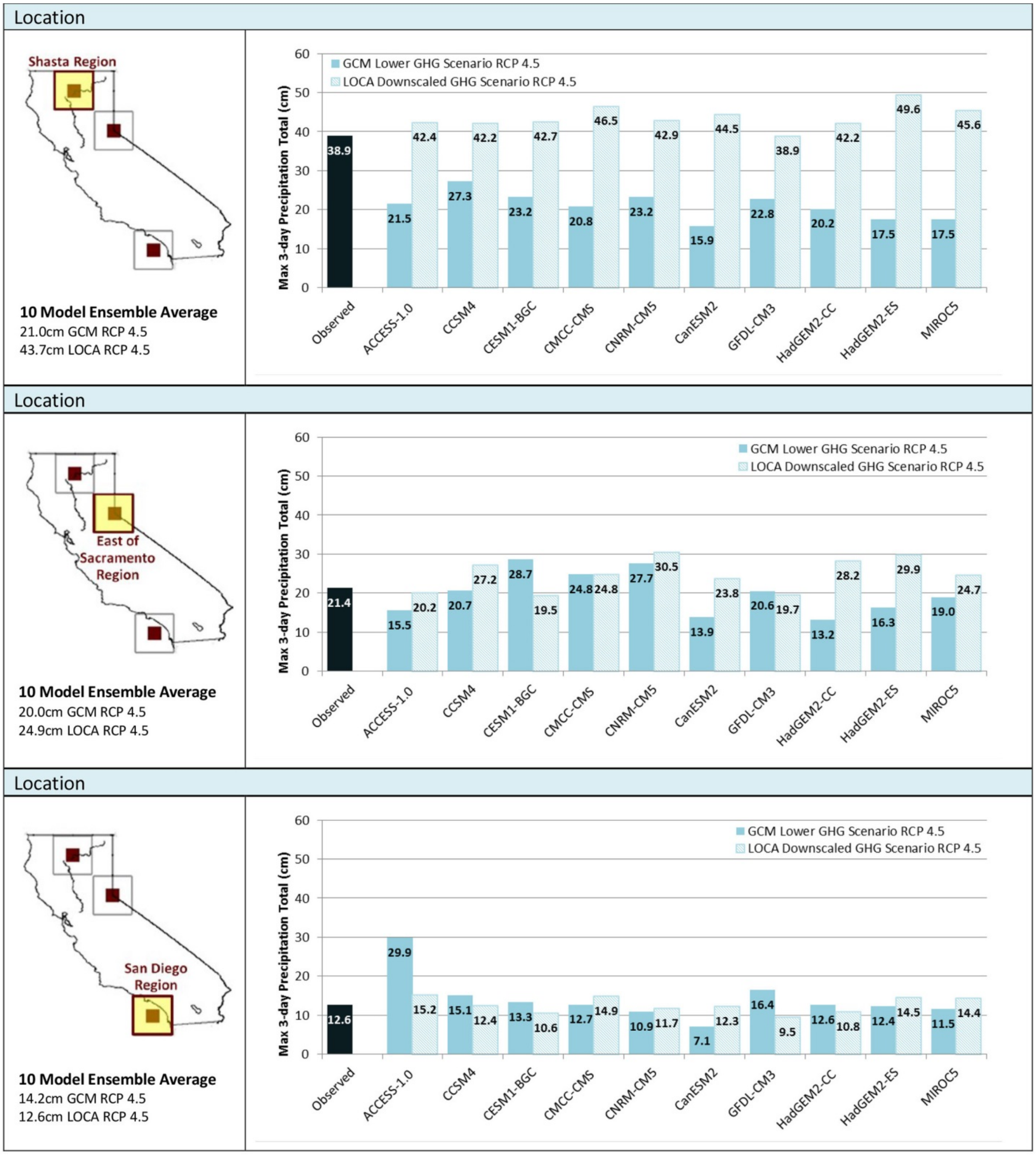
For a complete list of properties of the wettest decades (wettest year, number of wet years during the decade, comparison to historical conditions) for the 10 GCMs selected for use in California, see Tables B2-5 through B2-7. For GCM background information and affiliated research institutions, see the CMIP5 Coupled Model Intercomparison Project at http://cmip-pcmdi.llnl.gov/cmip5/availability.html.

Wettest 3-Day Periods

The simulated precipitation from the 10 selected GCMs was statistically downscaled using Localized Constructed Analogues (LOCA). The 3-day maximum precipitation was evaluated for both the GCM output directly and for the LOCA regionally downscaled output for both the historical period (WY1950-WY1999, see Chapter 4) and the future projection period (WY2006-WY2000). The wettest 3-day period precipitation is shown in Figure B2-5 for the lower future GHG scenario (RCP 4.5) and in Figure B2-6 for the higher future GHG scenario RCP (8.5).

For each of the three regions, Table B2-7a-c identify the wettest 3-day periods from the GCM output, and Table B2-8 a-c identify the wettest 3-day periods from the LOCA downscaled output for the same 10 models and three locations. In each case, the second column through the fifth column give information from the RCP4.5 simulations, and the sixth column through the ninth column give information from the RCP8.5 simulations. In each set, the four columns give (1) the wettest 3-day total, (2) the year that the 3-day period ends, (3) the month that the 3-day period ends, and (4) the day that the 3-day period ends. For comparison, the extreme precipitation during the wettest 3-day period observed in a corresponding 1/16° cell from the Livneh et al. (2013) dataset is shown in the last row of each table.

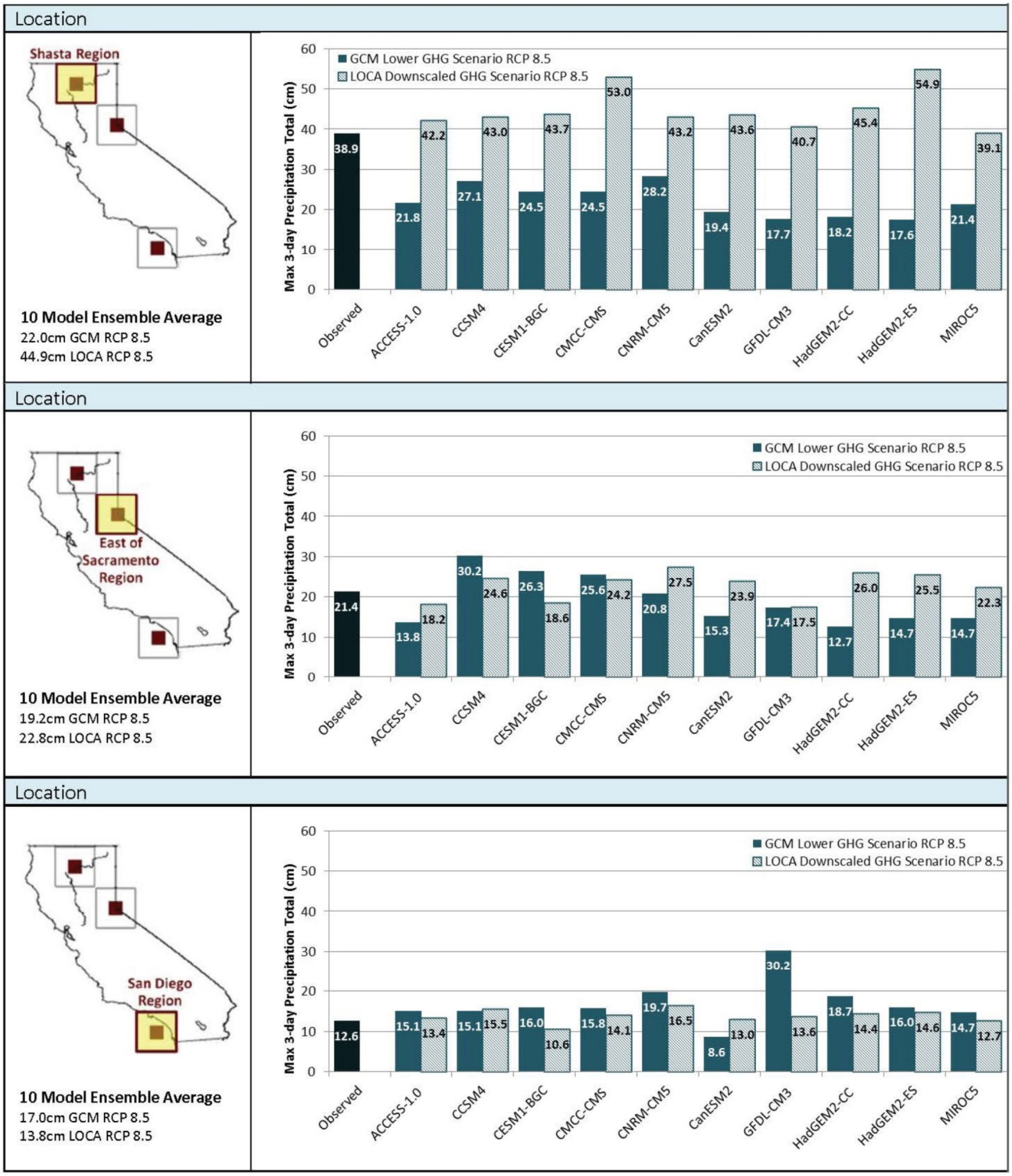
Figure B2-5 Future Maximum 3-Day Precipitation Simulated by Ten GCMs for the Lower GHG Scenario RCP 4.5



Notes: GCM = global climate model, GHG=greenhouse gas, LOCA= Localized Constructed Analogue downscaling method, RCP=Representative Concentration Pathway (refers to scenarios of future radiative forcings in 2100 of 4.5 Wm^2 and 8.5W/m^2)

Observed data are from Livneh 2013. LOCA data are preliminary and subject to revision. For GCM background information and affiliated research institutions, see the CMIP5 Coupled Model Intercomparison Project at http://cmip-pcmdi.llnl.gov/cmip5/availability.html.

Figure B2-6 Future Maximum 3-Day Precipitation Simulated by Ten GCMs for the Higher GHG Scenario RCP 8.5



Notes: GCM = global climate model, GHG=greenhouse gas, LOCA = Localized Constructed Analogue downscaling method, RCP=Representative Concentration Pathway (refers to scenarios of future radiative forcings in 2100 of 4.5 Wm^2 and 8.5W/m^2)

Observed data are from Livneh 2013. LOCA data are preliminary and subject to revision. For GCM background information and affiliated research institutions, see the CMIP5 Coupled Model Intercomparison Project at http://cmip-pcmdi.llnl.gov/cmip5/availability.html.

Table B2-7a Wettest 3-Day Future Periods Simulated by Ten Selected GCMs for the Shasta Region

Model Name	RCP 4.5					RCP 8.5				
	3-Day Total (cm)	3-Day Total / WY Clim* (%)	Year End	Month End	Day End	3-Day Total (cm)	3-Day Total / WY Clim* (%)	Year End	Month End	Day End
ACCESS-1.0	21.53	9.94	2053	1	22	21.76	10.05	2012	1	17
CCSM4	27.33	12.62	2093	2	3	27.05	12.49	2077	1	30
CESM1-BGC	23.21	10.71	2093	2	3	24.54	11.33	2034	1	13
CMCC-CMS	20.77	9.59	2006	12	7	24.50	11.31	2085	2	1
CNRM-CM5	23.23	10.72	2100	11	30	28.24	13.04	2097	12	29
CanESM2	15.86	7.32	2080	1	30	19.38	8.95	2089	1	10
GFDL-CM3	22.78	10.52	2063	2	14	17.68	8.16	2100	10	20
HadGEM2-CC	20.20	9.33	2066	1	4	18.21	8.41	2018	11	7
HadGEM2-ES	17.54	8.10	2037	11	17	17.56	8.11	2073	12	17
MIROC5	17.52	8.09	2067	12	16	21.40	9.88	2060	1	23
Livneh 2013	38.87	20.09	1956	2	22	38.87	20.09	1956	2	22

Notes:

GCM = global climate model, RCP=Representative Concentration Pathway (refers to scenarios of future radiative forcings in 2100 of 4.5 Wm2 and 8.5W/m2), WY = water year

For GCM background information and affiliated research institutions, see the CMIP5 Coupled Model Intercomparison Project at http://cmip-pcmdi.llnl.gov/cmip5/availability.html.

*WY climatology is simulated average annual precipitation for WY 1961-WY 1990.

Table B2-7b Wettest 3-Day Future Periods Simulated by Ten Selected GCMs for the East of Sacramento Region

Model Name	RCP 4.5					RCP 8.5				
	3-Day Total (cm)	3-Day Total / WY Clim* (%)	Year End	Month End	Day End	3-Day Total (cm)	3-Day Total / WY Clim* (%)	Year End	Month End	Day End
ACCESS-1.0	15.52	9.73	2075	1	20	13.75	8.62	2022	1	21
CCSM4	20.70	12.97	2032	11	25	30.18	18.91	2093	12	1
CESM1-BGC	28.67	17.97	2020	11	23	26.32	16.50	2034	1	13
CMCC-CMS	24.75	15.51	2095	1	31	25.57	16.03	2068	12	22
CNRM-CM5	27.66	17.33	2055	12	1	20.84	13.06	2097	12	29
CanESM2	13.90	8.71	2026	1	15	15.33	9.61	2086	1	26
GFDL-CM3	20.56	12.88	2063	2	14	17.41	10.91	2098	2	12
HadGEM2-CC	13.18	8.26	2077	2	19	12.68	7.95	2066	3	10
HadGEM2-ES	16.28	10.20	2050	12	18	14.72	9.22	2091	11	15
MIROC5	18.98	11.90	2020	2	2	14.73	9.23	2076	1	27
Livneh 2013	21.35	37.15	1955	12	24	21.35	37.15	1955	12	24

Notes:

GCM = global climate model, RCP=Representative Concentration Pathway (refers to scenarios of future radiative forcings in 2100 of 4.5 Wm2 and 8.5W/m2), WY = water year

For GCM background information and affiliated research institutions, see the CMIP5 Coupled Model Intercomparison Project at http://cmip-pcmdi.llnl.gov/cmip5/availability.html.

*WY climatology is simulated average annual precipitation for WY 1961-WY 1990.

Table B2-7c **Wettest 3-Day Future Periods Simulated by Ten Selected GCMs for the San Diego Region**

Model Name	RCP 4.5					RCP 8.5				
	3-Day Total (cm)	3-Day Total / WY Clim* (%)	Year End	Month End	Day End	3-Day Total (cm)	3-Day Total / WY Clim* (%)	Year end	Month End	Day End
ACCESS-1.0	29.88	49.19	2084	2	17	15.07	24.81	2079	10	20
CCSM4	15.05	24.77	2029	1	14	15.05	24.78	2077	1	25
CESM1-BGC	13.26	21.83	2055	3	17	16.00	26.34	2067	11	11
CMCC-CMS	12.71	20.93	2100	12	20	15.82	26.05	2051	9	17
CNRM-CM5	10.88	17.90	2087	11	22	19.74	32.49	2013	8	20
CanESM2	7.13	11.74	2032	1	19	8.57	14.11	2080	2	16
GFDL-CM3	16.42	27.03	2031	11	6	30.23	49.77	2075	12	1
HadGEM2-CC	12.55	20.66	2067	2	3	18.65	30.70	2063	11	18
HadGEM2-ES	12.35	20.33	2019	11	26	16.03	26.39	2035	2	1
MIROC5	11.51	18.95	2089	2	24	14.74	24.26	2071	1	18
Livneh 2013	12.57	45.22	1991	3	1	12.57	45.22	1991	3	1

Notes:

GCM = global climate model, RCP=Representative Concentration Pathway (refers to scenarios of future radiative forcings in 2100 of 4.5 Wm2 and 8.5W/m2), WY = water year

For GCM background information and affiliated research institutions, see the CMIP5 Coupled Model Intercomparison Project at http://cmip-pcmdi.llnl.gov/cmip5/availability.html.

*WY climatology is simulated average annual precipitation for WY 1961-WY 1990.

Table B2-8a **Wettest 3-day Future Periods from LOCA Downscaled Data for the Shasta Region**

Model Name	RCP 4.5					RCP 8.5				
	3-Day Total (cm)	3-Day Total / WY Clim* (%)	Year End	Month End	Day End	3-Day Total (cm)	3-Day Total / WY Clim* (%)	Year End	Month End	Day End
ACCESS-1.0	42.41	20.00	2056	10	6	42.20	19.90	2012	1	17
CCSM4	42.16	20.36	2097	2	25	43.02	20.78	2089	1	13
CESM1-BGC	42.65	20.48	2099	1	24	43.72	21.00	2050	2	15
CMCC-CMS	46.51	22.42	2085	12	7	53.02	25.55	2086	12	14
CNRM-CM5	42.94	20.50	2024	11	19	43.17	20.60	2093	2	21
CanESM2	44.49	22.13	2095	2	22	43.63	21.70	2091	1	29
GFDL-CM3	38.90	18.72	2065	11	18	40.73	19.60	2046	12	24
HadGEM2-CC	42.20	20.89	2086	2	17	45.40	22.47	2081	2	14
HadGEM2-ES	49.63	24.74	2088	4	9	54.91	27.37	2073	12	17
MIROC5	45.57	21.77	2030	1	9	39.08	18.67	2025	3	14
Livneh 2013	38.87	20.09	1956	2	22	38.87	20.09	1956	2	22

Notes:

GCM = global climate model, LOCA = Localized Constructed Analogue downscaling method, RCP=Representative Concentration Pathway (refers to scenarios of future radiative forcings in 2100 of 4.5 Wm2 and 8.5W/m2), WY = water year

For GCM background information and affiliated research institutions, see the CMIP5 Coupled Model Intercomparison Project at http://cmip-pcmdi.llnl.gov/cmip5/availability.html.

*WY climatology is simulated average annual precipitation for WY 1961-WY 1990.

Table B2-8b Wettest 3-day Future Periods from LOCA Downscaled Data for the East of Sacramento Region

Model Name	RCP 4.5					RCP 8.5				
	3-Day Total (cm)	3-Day Total / WY Clim* (%)	Year End	Month End	Day End	3-Day Total (cm)	3-Day Total / WY Clim* (%)	Year End	Month End	Day End
ACCESS-1.0	20.19	31.91	2075	1	21	18.20	28.77	2022	1	20
CCSM4	27.19	43.99	2009	1	24	24.63	39.85	2012	1	20
CESM1-BGC	19.49	32.05	2040	12	9	18.59	30.56	2017	12	17
CMCC-CMS	24.80	42.06	2010	1	7	24.21	41.06	2034	1	13
CNRM-CM5	30.54	50.61	2095	2	1	27.45	45.48	2085	2	2
CanESM2	23.81	40.42	2035	12	31	23.88	40.54	2023	1	20
GFDL-CM3	19.66	31.47	2063	2	14	17.45	27.94	2008	1	23
HadGEM2-CC	28.24	47.84	2079	1	28	26.02	44.08	2009	1	30
HadGEM2-ES	29.94	52.85	2050	1	16	25.53	45.07	2048	1	27
MIROC5	24.69	41.97	2020	2	2	22.31	37.94	2072	2	24
Livneh 2013	21.35	37.15	1955	12	24	21.35	37.15	1955	12	24

Notes:

GCM = global climate model, LOCA = Localized Constructed Analogue downscaling method, RCP=Representative Concentration Pathway (refers to scenarios of future radiative forcings in 2100 of 4.5 Wm2 and 8.5W/m2), WY = water year

For GCM background information and affiliated research institutions, see the CMIP5 Coupled Model Intercomparison Project at http://cmip-pcmdi.llnl.gov/cmip5/availability.html.

*WY climatology is simulated average annual precipitation for WY 1961-WY 1990.

Table B2-8c Wettest 3-Day Future Periods from LOCA Downscaled Data for the San Diego Region

Model Name	RCP 4.5					RCP 8.5				
	3-Day Total (cm)	3-Day Total / WY Clim* (%)	Year End	Month End	Day End	3-Day Total (cm)	3-Day Total / WY Clim* (%)	Year End	Month End	Day End
ACCESS-1.0	15.18	53.55	2075	2	3	13.37	47.15	2061	3	5
CCSM4	12.43	41.83	2032	1	19	15.53	52.25	2080	2	16
CESM1-BGC	10.60	41.50	2009	2	9	10.58	41.42	2076	2	21
CMCC-CMS	14.88	55.28	2030	1	13	14.05	52.20	2095	3	8
CNRM-CM5	11.71	40.85	2066	3	14	16.53	57.64	2054	1	14
CanESM2	12.29	45.47	2056	1	5	12.99	48.05	2086	1	4
GFDL-CM3	9.47	35.92	2027	3	29	13.64	51.73	2095	1	18
HadGEM2-CC	10.80	38.42	2016	3	2	14.41	51.28	2100	3	13
HadGEM2-ES	14.52	55.18	2055	2	4	14.62	55.58	2071	1	31
MIROC5	14.42	53.59	2089	2	23	12.69	47.18	2050	3	13
Livneh 2013	12.57	45.22	1991	3	1	12.57	45.22	1991	3	1

Notes:

GCM = global climate model, LOCA = Localized Constructed Analogue downscaling method, RCP=Representative Concentration Pathway (refers to scenarios of future radiative forcings in 2100 of 4.5 Wm2 and 8.5W/m2), WY = water year

For GCM background information and affiliated research institutions, see the CMIP5 Coupled Model Intercomparison Project at http://cmip-pcmdi.llnl.gov/cmip5/availability.html.

*WY climatology is simulated average annual precipitation for WY 1961-WY 1990.

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