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, over the South Western United States, and for specific needs for California water resources planning.

Key Point 2.3: This 3-step evaluation process identified 10 GCMs to 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 warrant possible revisions.

Additional findings from this GCM review process are listed below:

- 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 (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 the report Appendix.
- The screening process focused on data directly from the GCMs instead of examining data that had been downscaled to the regional scale so that the analysis would not be influenced by the choice of downscaling method.
- Although the criteria for the screening process did not consider if each GCM's results could be used for regional dynamical modeling (a form of downscaling the global results to the regional scale), 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.

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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; IPCC 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 to look 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 house gas 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 that 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 10 year 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.

However, GCM simulations are not perfect forecasts (e.g. Knutti 2008; Schmidt, G., 2009; Schmidt, G.A., and S. Sherwood, 2014). Climate projections are affected by different forms of uncertainty (Hawkins and Sutton 2011), including uncertainties in climate forcing such as aerosols and greenhouse gases (IPCC 2013), uncertainties in the model representation of the real climate system (Schmidt et al. 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 Intergovernmental Panel on Climate Change Report (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 or CMIP3 GCMs (note Appendix A3 provides a list of acronyms). 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 than those from the previous CMIP3 GCMs (e.g., IPCC AR5 WGI 2013; Polade et al 2013).

When the Climate Change Technical Advisory Group (CCTAG) exploration of climate model simulations began in 2013, simulations from 31 GCMs had been contributed to the CMIP5 archive. The 31 GCMs considered 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 available effort did not permit a re-visit of the additional available GCMs.

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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; IPCC 2013). Besides describing emissions, the RCPs also include land use change scenarios. There are four standard RCPs: RCP2.6, RCP4.5, RCP6.5, and RCP8.5, representing increases in end of century radiative forcings of +2.6, +4.5, +6.5, and +8.5 watts/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 to 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, we confine our investigation 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, over the South Western United States, and for specific needs for 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.

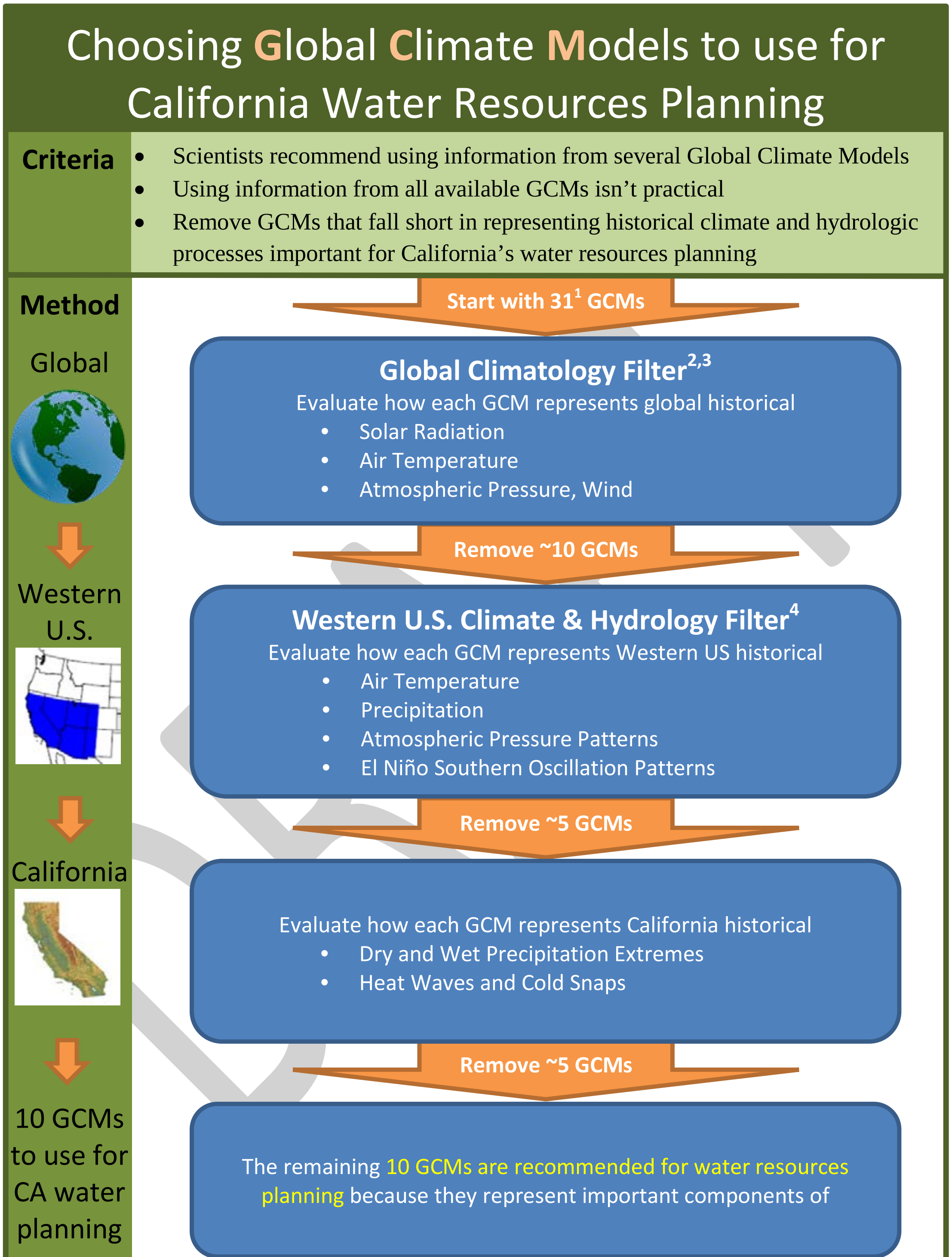
To select a smaller subset of models, a set of GCMs that perform reasonably well in simulating historically observed climate is desired. Importantly, there is evidence that it is not advisable to reduce the number of GCMs to a sample of simulations that is too small, because it has been shown that several (order 10 models) GCMs are needed to describe the rather wide distribution of possible climate variations and changes that could occur in future 10 year periods (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, we follow previous studies in adopting the “direct approach” of model evaluation (5th IPCC WG1 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 in order 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 evaluates GCM simulations of historical climate at the global and Western United States scales. After work by Gleckler (2008), IPCC 2013 and Rupp et al. 2013, an evaluation is conducted based on a collection of scalar metrics to gage 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 U.S. 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 there is not a strong relationship between model performance and the model’s climate sensitivity (IPCC, 2007). Second, there is no strong evidence that indicates 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 gage the suitability of a climate model other than its performance in simulating observed climate. Thus this effort evaluated GCM simulations of historical climate relative to selected metrics. The models were NOT evaluated on any characteristics of their future projections. Similar to mutual funds in economics, although 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



References:

[1] CA-DWR Climate Change Technical Advisory Group analysis used GCMs available at the start of the investigation that met certain data requirements (2013).

[2] Gleckler, P. J., Taylor, K. E., and Doutriaux, C.: Performance metrics for climate models, J. Geophys. Res.-Atmos. (2008).

[3] IPCC, Climate Change 2013: The Physical Science Basis, Cambridge University Press, Cambridge, UK and New York (2013).

[4] Rupp, D. E., J. T. Abatzoglou, K. C. Hegewisch, P. W. Mote: Evaluation of CMIP5 20th century climate simulations for the Pacific Northwest USA, J. Geophys. Res.-Atmos. (2013).

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 (S) & Longwave (L) 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*-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**, 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 Niño3.4 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** precipitation 1961-1990 (%)
El Niño Pattern Correlation	Spatial structure of correlation of precipitation to the Nino 3.4 ENSO index derived from a GCM, gaged by pattern correlation to that from historical observations
El Niño temporal variation	Nino 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

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

**Water years are October to September instead of the calendar year from January to December

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
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.

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			

*Note that this is not a comprehensive evaluation of GCM performance. The evaluation was targeted at reducing the number of GCMs to use in California water resources planning.

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Evaluating GCMs using Global Metrics

A set of 31 CMIP5 Global Climate Models was evaluated using a set of global metrics for longwave and shortwave radiation, winds, precipitation and temperature (Table 2.1) (Gleckler, 2008). Results are shown in Figure 2.2 (IPCC 2013), an analysis contributed by Gleckler and colleagues patterned after Gleckler et al. 2008. The analysis presented in IPCC 2013 defined the global evaluation metrics and assessed each GCMs performance relative to those metrics and root mean square error (RMSE) results were calculated. Consulting the results from this screen (Figure 2.2), 19 GCMs were accepted (Table 2.2). The subset of models that were not included was removed from consideration because of poor skill in replicating global scale winds, geopotential height structure, radiation, and temperature. During this stage of the screening process, consideration of model "genetics" came into play (see below), wherein the Hadley Center HadGEM2-AO GCM was excluded and the GFDL-CM3 GCM was included.

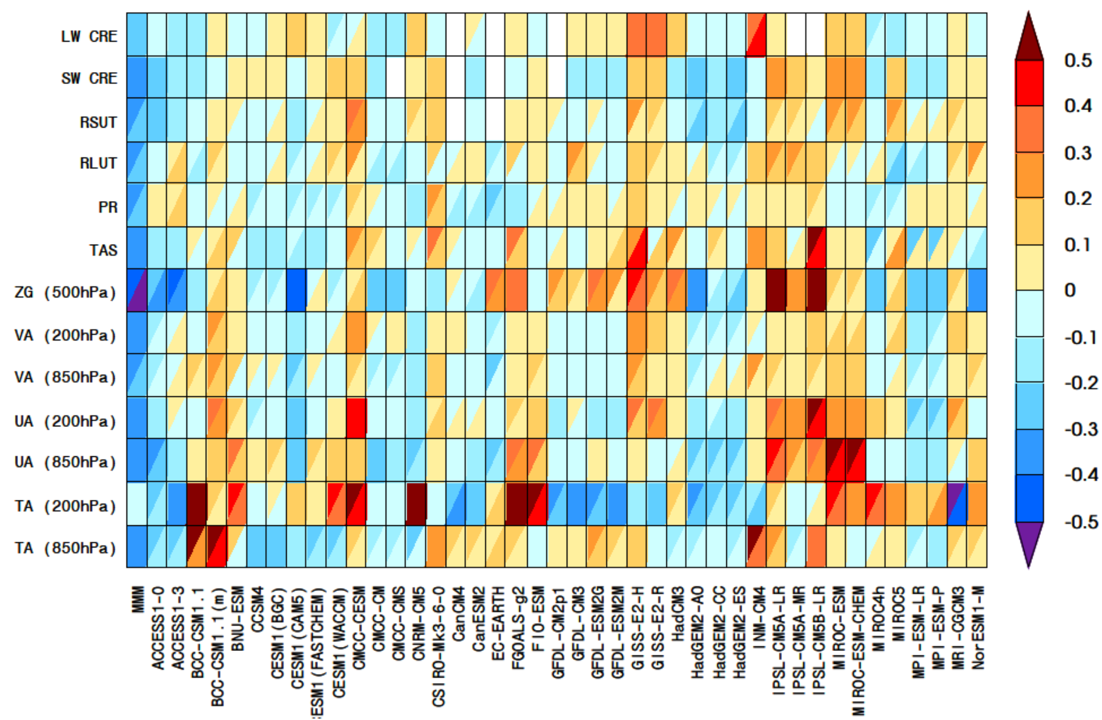
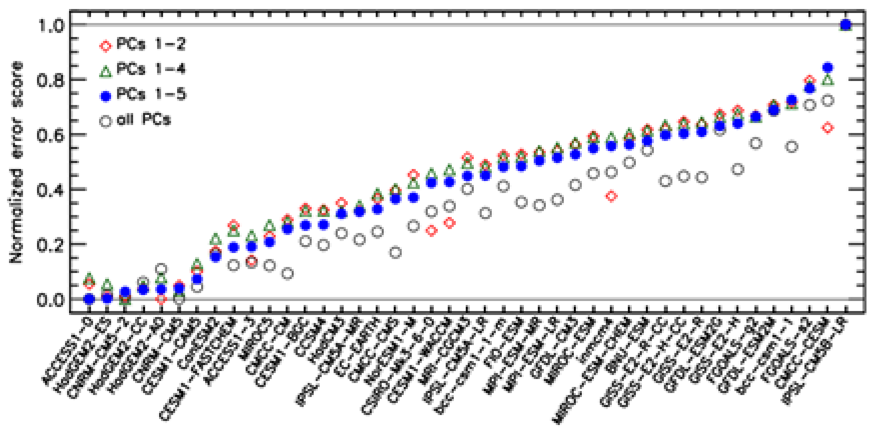


Figure 2.2: Analysis of GCM Representation of Historical Climate using Global Scale Metrics
Reproduction of Figure 9.7 from IPCC AR5 WG1, Chapter 9 (IPCC 2013): Relative error measures of CMIP5 model performance, based on the global seasonal-cycle climatology (1980-2005) computed from the historical 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 IPPC (2013).

Evaluating GCMs using Regional Metrics for the Southwest U.S.

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 Rupp et al. 2013. CCTAG's regional assessment used information from this screening procedure which had been applied to the Southwest U.S. for nearly all of the CMIP5 GCMs evaluated (Rupp, personal communication). As a result, (Figure 2.3), an additional 4 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.

a) Evaluation with 22 metrics



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

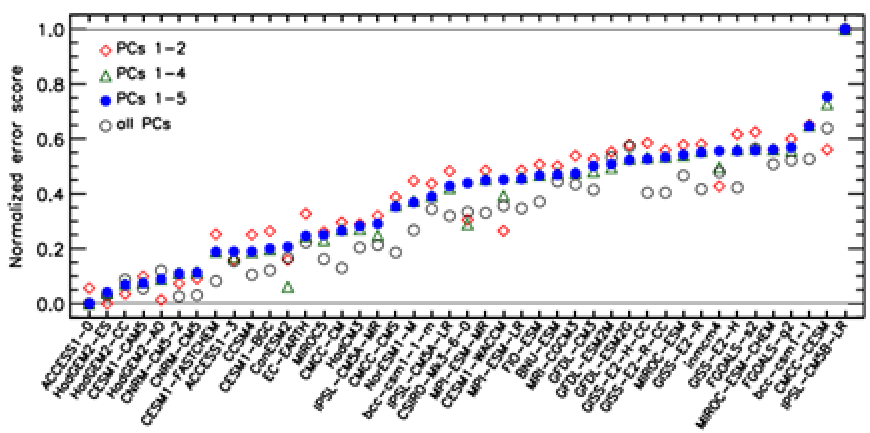


Figure 2.3: Ranking of GCMs based on regional performance metrics

Source: David Rupp GCM evaluation for Southwest U.S. personal communication: 43 CMIP5 GCMs ranked according to normalized error score from empirical orthogonal function (EOF) analysis of performance metrics. Ranking is based on the first 5 principal components (PCs, filled blue circles). The open symbols show the models' error scores using the first 2,4, and all 22 principal components The best scoring model has a normalized error score of zero.

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 El Niño Southern Oscillation (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 that is used to drive water resources models and specific types of conditions and variability that effect water resource 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 1961-1990. For example a value of 0.25 would mean that the maximum 3 day precipitation represents 25% of the average historical annual precipitation.
- ***El Niño-Precipitation Pattern Correlation:*** the degree of similarity, from a GCM vs. observations, of the pattern formed from correlations between the Nino 3.4 sea surface temperature (a commonly used index of El Niño/Southern Oscillation 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.
- ***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 gage how well a model represents the temporal pattern of the El Niño Southern Oscillation (ENSO). Models that had ENSO patterns that occurred too regularly, for example an el Niño every 4 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. Knutti et al. (2013) describes "model genetics" of CMIP5 GCMs, providing some insight into the degree of similarity between CMIP5 GCMs. In the CCTAG screening exercise, we tried to avoid redundancy by not selecting more than two GCMs from the same modeling group. And, we tried to increase diversity by including models that might otherwise have been eliminated by one of the screening metrics. Thus, consideration of model "genetics" led us to exclude the Hadley Center HadGEM2-AO GCM to avoid 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

GCMs in this subset are those which remained after global and regional screening. Those GCMs with grey shading were discarded based upon one or more (orange colored) 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	

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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 5 GCMs (Table 2.3). GCMs that were not accepted by the California screens were excluded because of unrealistic El Nino/Southern Oscillation 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, Southwest United States and adjacent regions, and California region water management relevant climate measures. The 10 CMIP5 GCMs that passed the collective screening process are:

ACCESS-1.0	CNRM-CM5	HadGEM2-CC
CCSM4	CanESM2	HadGEM2-ES
CESM1-BGC	GFDL-CM3	MIROC5
CMCC-CMS		

Some details about these 10 models are presented in Table 2.4 of the Individual Model Characteristics section later in this chapter.

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 GCM's of the larger set of 31 models?

In order to investigate how the ensemble of ten selected GCMs compares to 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 total) over the California/Nevada region, are shown in Figure 2.4. Three grid cells were selected for the comparison analysis: centered at 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.

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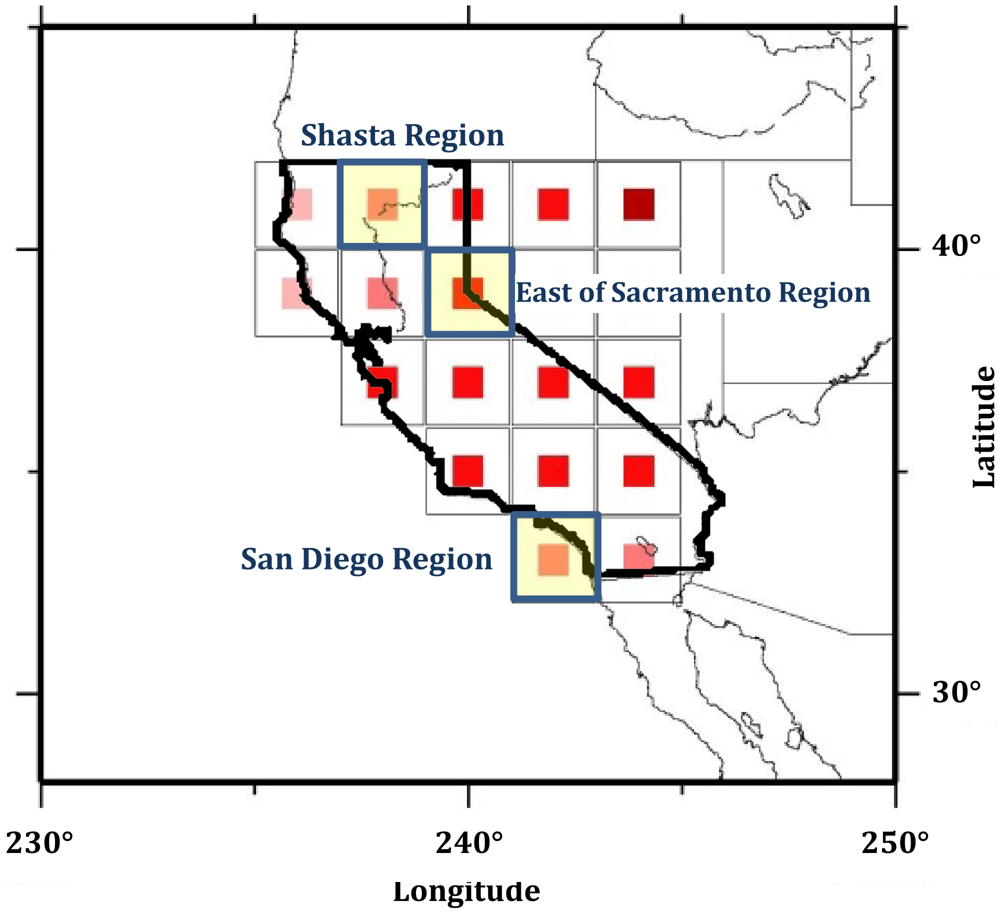

Figure 2.4: Uniform 2° grid upon which data from each of the 10 GCMs was interpolated. The three highlighted locations were selected for presentation in this report.

Pertinent to the selection of a subset of GCMs for California water resources 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 to 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 to the envelope of those of the overall 31 member ensemble. Second, temperature vs precipitation changes 2070-2099 vs 1961-1990 for the 10 selected GCMs compared to the remaining 31 GCMs are plotted in Figure 2.7. For both sets of figures, results are shown for both 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 warmer than historical mean compared to an overall range of 3°F to 6.5°F 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 greater than historical mean compared to an overall range of 5.5°F to 10.5°F for the large ensemble of 31 GCMs.

From the 10 selected models, the East of Sacramento Region precipitation changes 2070-2099 vs 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% to 125% of historical mean compared to an overall range of 85% to 125% for the large ensemble of 31. However, 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% to 130% of historical mean compared to an overall range of 75% to 130% for the large ensemble of 31.

From this rather cursory comparison of future projections of temperature and precipitation, **we conclude that the 10 selected GCMs represent a similar magnitude and spread of temperature and precipitation change over the 21st Century as the full set of 31 CMIP5 GCMs evaluated.** However 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 these 10 models.

A similar analysis was also conducted to compare the 10 selected GCMs to the 6 CMIP3 GCMs that were employed in the 3rd California Climate Change Assessment (see Appendix A1). That analysis found that these two sets of models produced similar ranges of temperature and precipitation change over the 21st Century.

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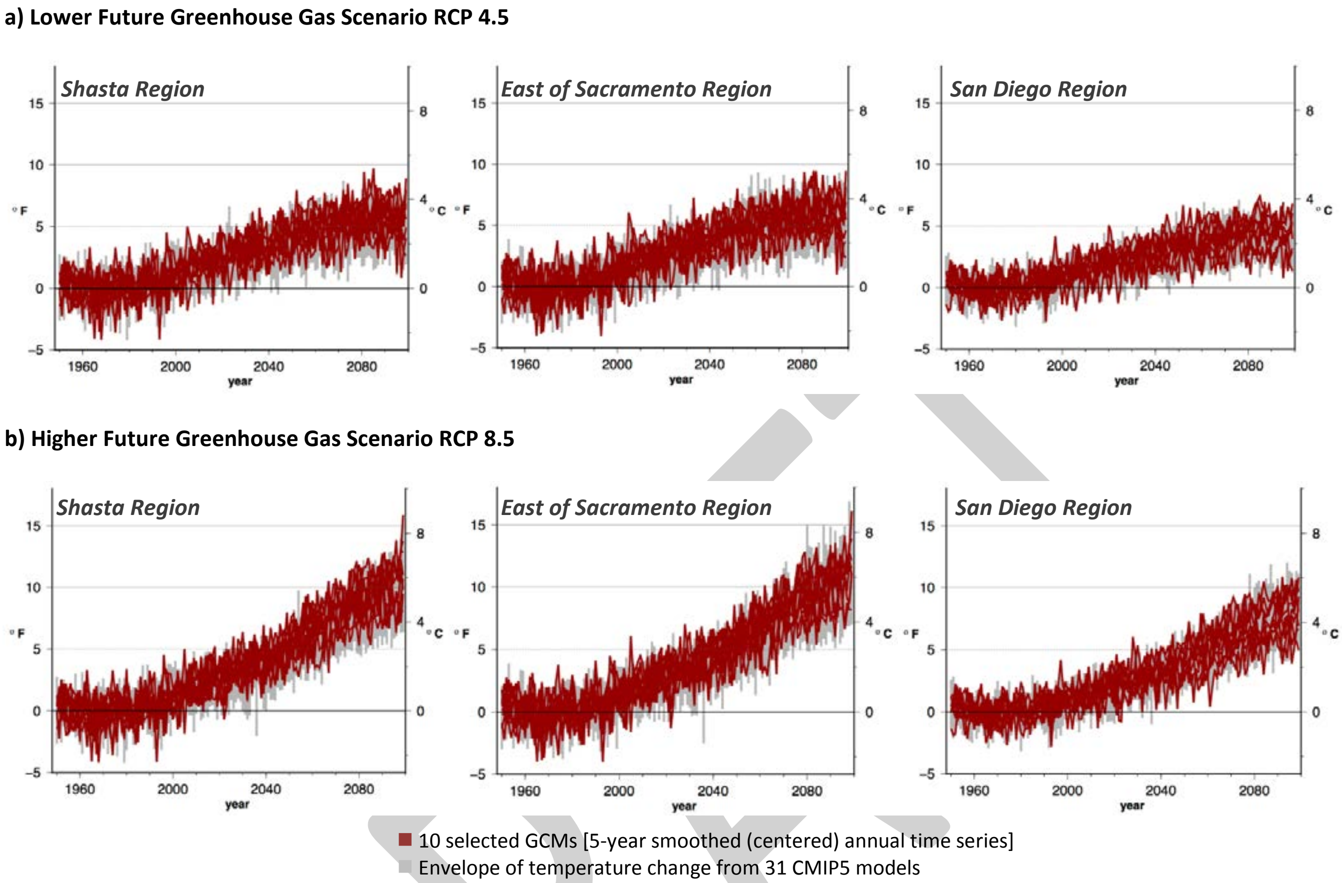

Figure 2.5: Annual change in temperature from GCM simulations relative to 1961-1990 climatology

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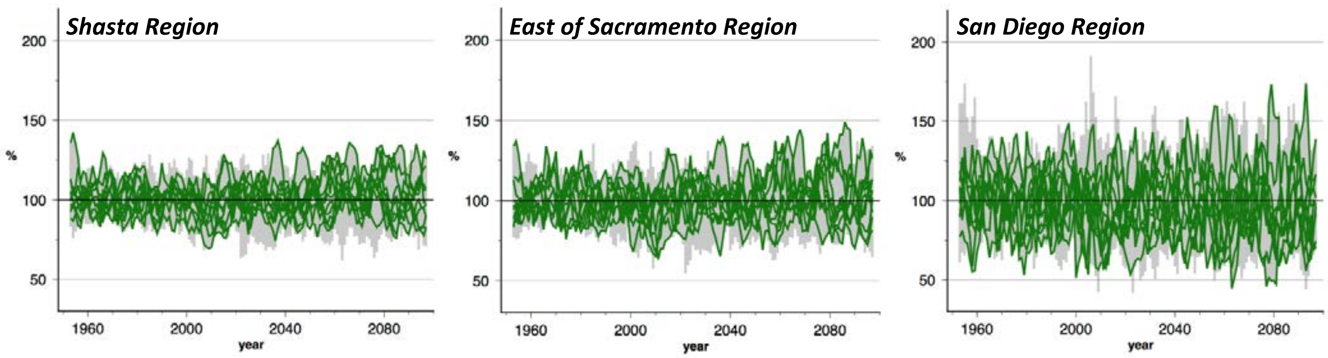
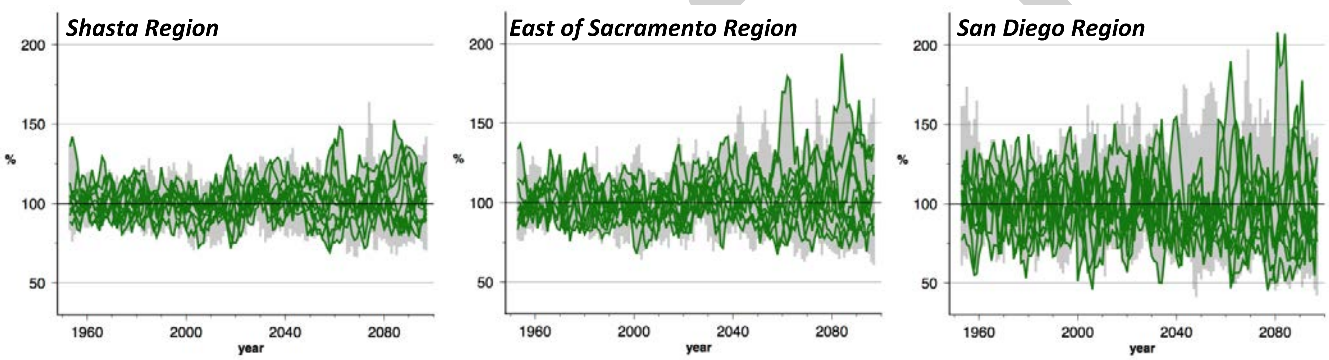
a) Lower Future Greenhouse Gas Scenario RCP 4.5



b) Higher Future Greenhouse Gas Scenario RCP 8.5



■ 10 selected GCMs [5-year smoothed (centered) annual time series]
■ Envelope of precipitation change from 31 CMIP5 models

Figure 2.6: Water year precipitation as the percent of historical 1961-1990 precipitation climatology
Values greater than 100% indicate an increase in precipitation relative to the historical average, and values less than 100% indicate a decrease in precipitation relative to the historical average. Water years are October-September.

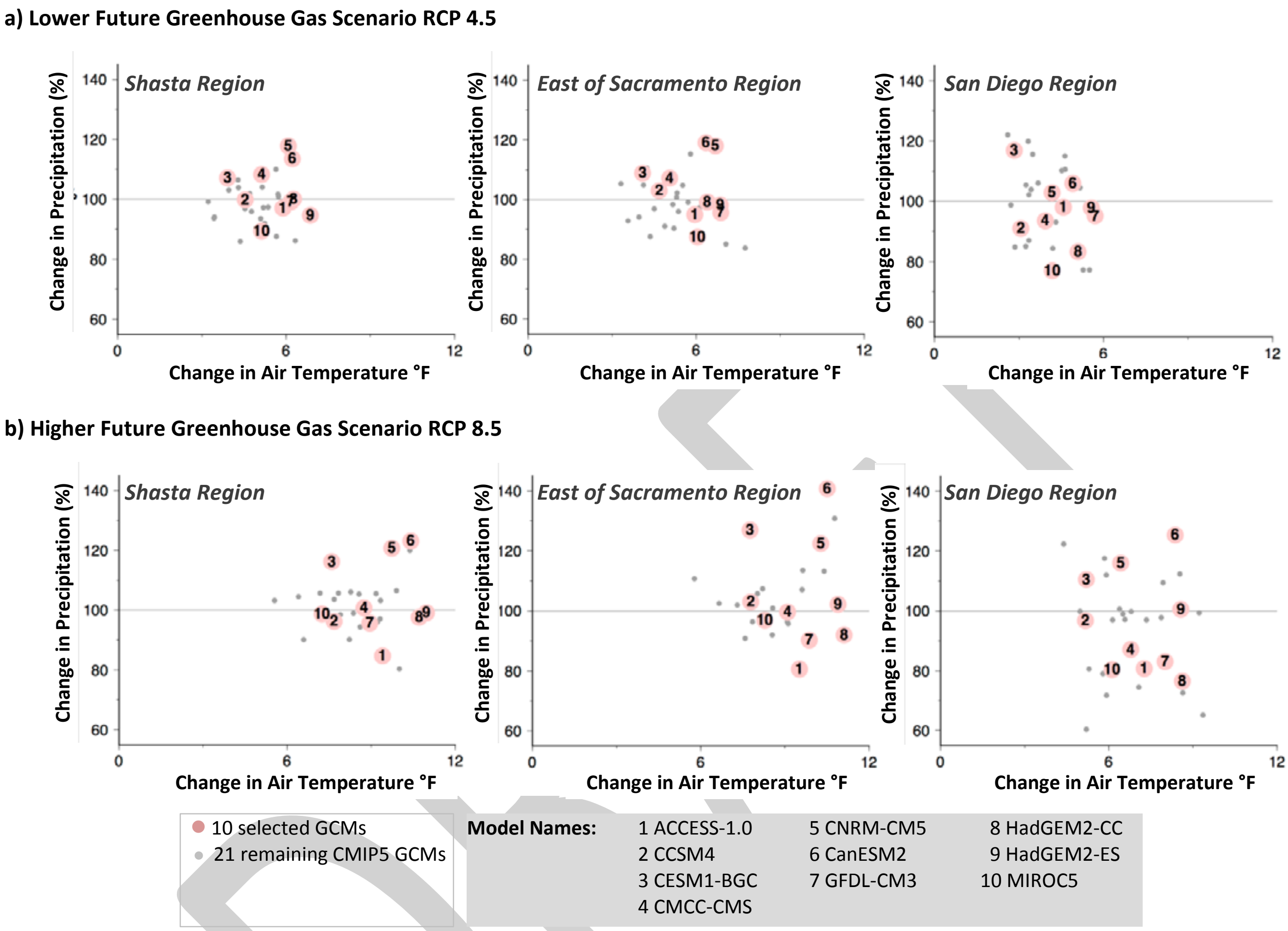


Figure 2.7: Late century temperature and precipitation changes 2070-2099 vs 1961-1990 historical climatology
Values greater than 100% indicate an increase in precipitation relative to the historical average, and values less than 100% indicate a decrease in precipitation relative to the historical average.

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:

- 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 A2)

Model Resolution and Dynamical Downscaling Suitability

For the 10 Global Climate Models 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 km to 250 km.

The evaluation process for selecting 10 GCMs for California did not consider whether a given GCM provided output data that was sufficient to serve as boundary conditions for driving regional climate model (RCM) simulations ("dynamical downscaling"—see 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, 8 of the GCMs did save and do provide data necessary to support RCM runs (McSweeney et al 2012), as noted in Table 2.4.

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Table 2.4: Characteristics of GCMs selected for California water resources planning

Models are listed alphabetically.

Model number	Model name	Model Institution	Model resolution*	Dynamical downscaling**
1	ACCESS-1.0	CSIRO (Commonwealth Scientific and Industrial Research Organization, 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)	✓

* size of the model's atmospheric grid (number of longitudes by number of latitudes)

**A check mark indicates that the model has the necessary variables at the proper time interval for dynamical downscaling

End of 21st Century change in Temperature and Precipitation

Table 2.5 shows changes (2070-2099 vs. 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 to be toward becoming drier toward Southern California and becoming wetter toward Northern California.

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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

Red shading indicates model simulations that show relatively high warming;
olive shading indicates simulations that show drying.

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	5.95	9.52	-1.45	-5.59
CCSM4	4.68	7.79	1.27	1.28
CESM1-BGC	4.09	7.76	3.55	10.79
CMCC-CMS	5.06	9.09	3.27	-0.17
CNRM-CM5	6.69	10.28	7.93	9.90
CanESM2	6.35	10.51	3.71	7.94
GFDL-CM3	6.83	10.07	-2.00	-4.53
HadGEM2-CC	6.39	11.10	-0.19	-1.80
HadGEM2-ES	6.87	10.89	-0.37	0.45
MIROC5	6.05	8.29	-3.80	-0.96

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, while warming under RCP 8.5 ranges from 7.7°F to about 11°F. To large extent, the models which trended drier over the 21st Century under RCP 4.5 were the same models which dried under RCP 8.5. Precipitation changes under RCP 4.5 ranges from about -4 inches to +8 inches different from the historical climatology of annual average precipitation, and under RCP 8.5 ranges from about -5.6 inches to +10.8 inches 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 GMC simulations provide a set of temperature increases and precipitation changes that fall into a similar range as those from 6 CMIP3 GCMs that were employed in the previous California Climate Change Vulnerability and Adaptation Assessment, as illustrated in Appendix A2.

Individual Model Wet and Dry Spell Characteristics

For some applications, extreme wet or dry long term conditions may be critical for analysis purposes. To this end, the precipitation projections from the 10 selected GCMs were evaluated (Appendix A2) 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 4 and as many as 8 dry years in a 10 year period.

- The wettest 10-year periods identified from the set of GCM simulations contained as few as 4 and as many as 10 wet years in a 10 year period.

- Maximum three day wet spells provided by the GCMs were consistently lower than those from observed data. However 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 A2.

Summary and Conclusions

This chapter presents a methodology for reducing a larger set of Global Climate Models 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.

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