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Creating Climate projections to support the 4th California Climate Assessment

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EXECUTIVE SUMMARY

We have generated daily, 1/16° spatial resolution (about 6 km, or 3.7 miles) climate projections over the state of California to support the 4th California Climate Assessment. We started with data from 32 coarse-resolution global climate models (GCMs) from the Climate Model Intercomparison Project, version 5 (CMIP5) archive, which is the most recent archive of models developed for the United Nations Intergovernmental Panel on Climate Change reports. The data cover 1950-2005 for the historical period, and include two future climate projections for the period 2006-2100, one using medium (Representative Concentration Pathway [RCP] 4.5) and one using high (RCP 8.5) greenhouse gas and aerosol emissions scenarios. We removed systematic errors from the GCMs via bias correction and then downscaled the daily precipitation, minimum and maximum temperature data from the coarse-resolution GCMs to the 1/16° latitude-longitude grid using a statistical method called Localized Constructed Analogs (LOCA). The downscaled fields were applied to the VIC land surface/hydrological model to develop additional variables of interest to climate impact studies, including snow cover, soil moisture, runoff, water loss from plants, surface heat fluxes, etc. The final data set of 32 models is voluminous (~40 TB), so recommendations are included for selecting a subset of models if the full set cannot be accommodated. A subset of 10 models identified by the California Department of Water Resources as having a good simulation of California's climate is described. For impact studies that cannot accommodate data from 10 models, a further reduced set of 4 models that substantially cover the results from the set of 10 is derived.

1. Purpose

The purpose of this document is to describe the process of creating daily high-resolution (1/16°) climate projections to support the 4th California Climate Assessment effort. We indicate how the relevant global climate models were selected, briefly discuss the LOCA statistical downscaling and VIC hydrological modeling methods used, list what variables are available to the impacts research community, and provide general guidance on how to pick models for impact studies. Modest familiarity with the basics of climate model projections is assumed.

2. Overview

A robust climate assessment relies on multiple scenarios of future climate from the most current global climate models (GCMs) available. The most recent archive of GCM data is CMIP5, developed to support the work of the United Nations Intergovernmental Panel on Climate Change. The 32 GCMs used in the current work, from a variety of domestic and international institutions, are described in section 3.

Although GCMs form the basis of a future climate assessment, they cannot be directly used for impact studies. This is because GCMs have systematic errors, termed biases, in their output that can invalidate impact studies if not accounted for. For example, California's annual precipitation in a GCM may be 30% too high, or the summer temperature might be several degrees too low. These biases are removed by a process known as bias correction (section 4.1). Secondly, global models have spatial resolution that is too coarse to be directly useful for California's needs. For example, Figure 1 (left panel) shows the representation of California's topography in a typical climate model. The resolution cannot adequately capture California's diverse topography, which is important to many climate impacts in the fields of energy demand, human health, agriculture, and ecosystem impacts.

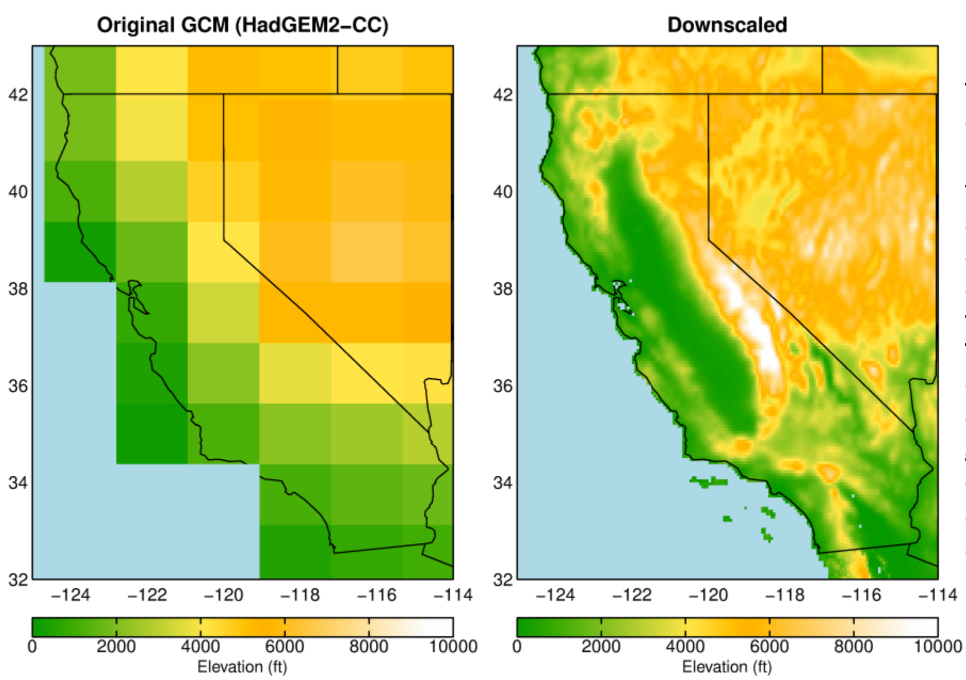

Figure 1. Left: Topography in a typical Global Climate Model (GCM). Major land features of California, such as the Sierra Nevada and Central Valley, are almost entirely absent in the global models. Right: Topography after downscaling to the 1/16th degree (6 km, or 3.7 mile) grid. At this scale not only the Central Valley and Sierra Nevada, but also details of the coastal ranges are captured.

To address the problem of coarse spatial resolution in GCMs, the climate research community typically uses a processes termed “downscaling”, which transforms the GCM data to a much finer spatial scale. The current work uses a new downscaling technique called LOCA (section 4.2) with a spatial resolution of 1/16th degree latitude-longitude, which is about 6 km (3.7 miles). The model topography after downscaling is shown in the right panel of Figure 1. LOCA was developed to address problems in the downscaled data used in previous California Climate Assessment efforts, and with support from the California Energy Commission

The LOCA downscaling provides a limited set of meteorological variables, including daily precipitation, daily maximum and minimum temperature, and, as the appropriate methods are developed, wind speed and specific humidity. However, impacts studies often need more variables, such as snow cover (for examining water supply issues), soil moisture (relevant to agriculture and droughts), and relative humidity (for human health, ecosystem, and wildfire impacts). Some of these additional variables are developed using the Variable Infiltration Capacity (“VIC”) land surface model. The VIC modeling process is described in section 5. The full list of variables available from this work is given in Appendix 2.

Finally, the sheer amount of data generated in this process can be daunting for impact studies. There are 32 models, each with daily data covering the state of California over a historical period of 1950-2005 and two future projections from 2006-2100 (one with lower greenhouse gas emissions and one with higher). Recognizing that not all impacts groups will be able to use the full set of 32 models, we have also developed selection criteria designed to span the range of the best-performing models over the California domain. This results in a recommended set of 4 models that are a sensible choice to use if all 32 models cannot be accommodated. The models and selection process are described in section 6.

3. The Global Climate Models (GCMs)

The most recent research community archive of GCM results is the CMIP5 archive (Taylor, 2012). Any institution can contribute data to CMIP5; there is no vetting of model quality before the data is added to the archive. As a practical matter, though, the significant amount of resources needed to develop and run a GCM means that most models represent a large amount of work from many collaborating climate scientists. Picking the ”best” GCMs for California applications is addressed in section 6.

At the time that work on the California climate scenarios was started, CMIP5 incorporated data from approximately 40 models. However, one of the objectives of this project was to provide daily data, since many important climate impacts arise from daily extremes. For example, heat waves that affect peak energy demand or human health, Santa Ana winds, and heavy precipitation days that cause flooding are all sensitive to individual daily extremes. We therefore limited the selection of GCMs to those that provided daily precipitation, and maximum and minimum temperature. This requirement resulted in a set of 32 GCM, which are shown in Appendix 1.

The historical period of the CMIP5 GCMs ends in 2005. Two scenarios of how societies might act in the future, including their response to the problem of global climate change, are included in the data set. Representative Concentration Pathways (RCPs) 4.5 and 8.5 are designed to be scenarios of medium and high future greenhouse gas and aerosol emissions, respectively, over the period 2005-2100. It is worth

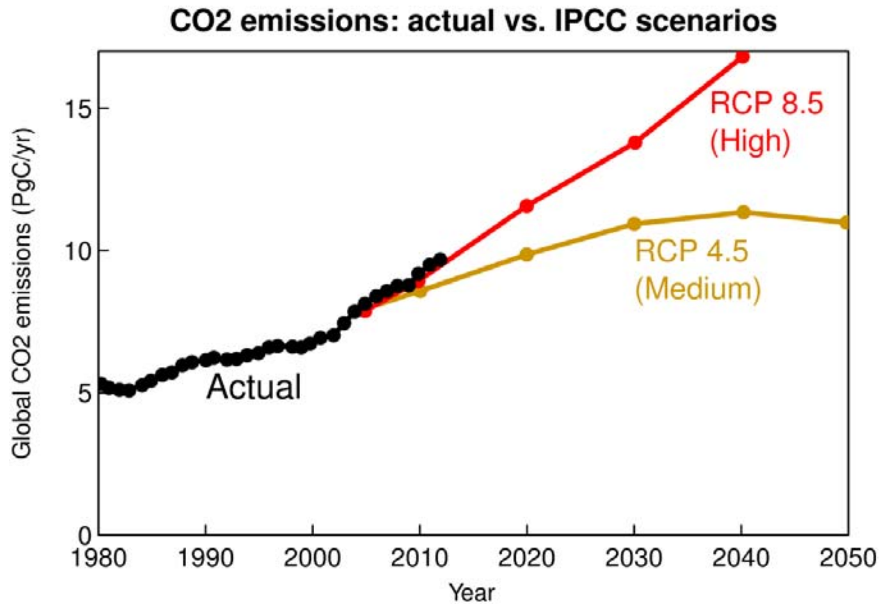

Figure 2. Actual carbon dioxide emissions (black dots) compared to the trajectories used in the IPCC "high" (RCP 8.5, red) and "medium" (RCP 4.5, gold) emissions scenarios. Current emissions are slightly above the highest trajectory considered in the last IPCC report. Redrawn from Peters et al., Nature Climate Change, 2013.

noting that current emissions are above the level represented by RCP 8.5 (see Figure 2), which is the highest emissions scenario considered in the last United Nations IPCC Climate Assessment (IPCC, 2013).

4. Bias correction and spatial downscaling

4.1 Bias correction

Bias correction is the process of reducing systematic errors in climate simulations, in this case as a result of errors or inadequacies in a GCM. Left as is, these errors would wreak havoc on climate impact studies, particularly when simulating impacts that have a non-linear response to climate forcing. For example, a medium amount of precipitation might soak into the soil and produce little runoff and minimal risk of flooding, while twice as much precipitation could exceed the moisture holding capacity of the soil and produce far more than twice as much runoff. In such a case, estimates of flooding will be very sensitive to errors (biases) in the model's simulated precipitation. A typical example of precipitation biases in a GCM is shown in Figure 3.

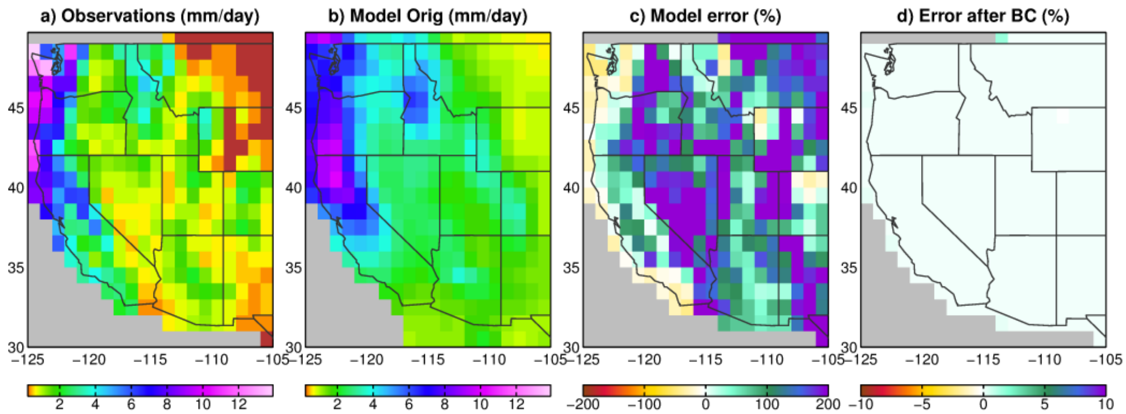

Figure 3. Example of biases (systematic errors) in a GCM, illustrated for average December precipitation (1950-2005) using the CCMS4 GCM. a) Observations (mm/day, from Livneh et al. 2015). b) The original model field. c) The model error with respect to the observations (%). d) The model error after the bias correction process is completed (%). Note that the color range in panel d) is much smaller than that in panel c).

For the California 4th assessment we developed new techniques of bias correction that perform better in removing these systematic GCM errors than was used in the previous assessment (Pierce et al., 2015). The new bias correction has the following properties.

First, for each climate variable (temperature, precipitation, etc.), the amount of variability seen in different frequency bands is adjusted to match observations. For example, a GCM might have too much day-to-day precipitation variability, but too little year-to-year variability. This error affects the model's simulation of floods and droughts. Analogous errors in temperature can affect the simulation of heat waves. The frequency dependent bias correction reduces these errors. This process is illustrated in Figure 4 for daily maximum temperatures at a location along the California coast (purple x in Figure 4, left panel).

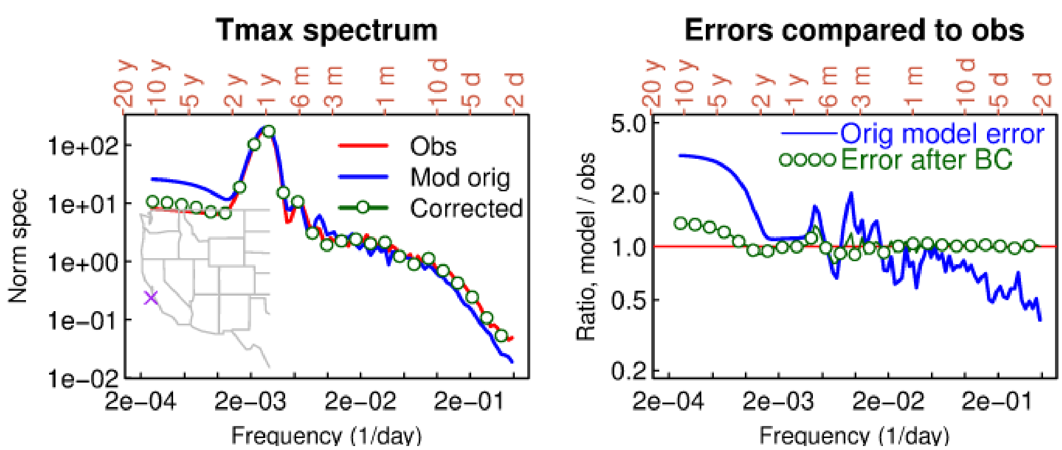

Figure 4. Illustration, using daily maximum temperature, of how the bias correction reduces errors in the model's simulated variability in different frequency bands (daily, monthly, yearly, decadal, etc., as shown in the orange lettering along the top of the panels). Left panel: The original spectra (variability as a function of frequency) in the observations (red), uncorrected model (blue), and corrected model (green line and dots). Right panel: The error in model simulated variability compared to the observations, expressed as a ratio (so "1" means no error, "2" means twice as much variability as observed, etc.). From Pierce et al., 2015.

Second, this bias correction scheme is designed to largely preserve the original GCM's climate change projections. Although it may seem odd, many previous forms of bias correction change the GMC's future climate in ways that have no physical basis (Maurer and Pierce, 2013). For example, quantile mapping, the bias correction technique used in several previous datasets used by earlier California state climate assessments, increases projected winter precipitation changes in the entire Northwest part of the country by up to 30% (Pierce et al., 2015). The bias correction developed for this work does not appreciably alter the GCM's climate projections.

Finally, the present bias correction improves over previous techniques that generally had to compromise between getting an accurate representation of the annual cycle and properly representing seasonal extremes. The present bias correction uses a new technique to better represent both the seasonal cycle and seasonal extremes simultaneously.

An example showing the result after these bias correction steps have been applied to mean December precipitation is shown in Figure 3 (panel d). While the original model errors in December average precipitation exceeded 200% over much of the interior western U.S. (Figure 3c), after bias correction the mean error is almost zero (Figure 3d).

4.2 Spatial Downscaling

Downscaling is the process of transforming the coarse spatial resolution GCM data to a finer spatial scale, which here is $1/16^{th}$ of a degree in latitude and longitude (about 6 km, or 3.7 miles). For this project we developed a new form of statistical downscaling called "Localized Constructed Analogs", or LOCA (Pierce et al., 2014), that has been designed to improve upon certain spatial and temporal aspects of previous analogue downscaling methods.

Statistical downscaling approaches use observed historical relationships between broad-scale climate measures and local climate measures to downscale a GCM's pattern of precipitation or temperature. The assumption in all statistical downscaling techniques is that the historically observed relationships between local and regional measurements will continue into the future.

Statistical downscaling is relatively inexpensive compared to dynamical downscaling, which uses a full numerical model similar to a weather forecast model. Using statistical downscaling allows us to downscale 32 GCMs, which would be prohibitively expensive with dynamical downscaling. For the observed data set, which is used to train the statistical model, we used the Livneh et al. 2015 data over the period 1950-2005. Although the Livneh data set extends to 2013, we only include data up to 2005 in order to match the historical period of the CMIP5 GCMs.

Constructed analog downscaling techniques such as LOCA identify historical days that are similar to the GCM data being downscaled (these days are called the analog days), and then assume that the relationship between, for example, the regionally-averaged temperature and the temperature at a particular station is the same in the future as it was on the selected historical analog day. For example, a station at a higher elevation than most other stations in the region will be systematically colder than the regional temperature average; statistical methods assume this relationship maintains in the future.

Constructed analogs are typically applied in a conceptually straightforward manner: to downscale a model day, the 30 observed days that best match the model day over the entire domain are found, then optimal weights for the 30 observed days are computed such that the combination best reproduces the model day. Finally, the downscaled field is obtained by combining the original fine-resolution observed fields using those same optimal weights.

Conceptually, LOCA is nearly as straightforward: to downscale a model day, the 30 observed days that best match the model day in the wider region around the point being downscaled are found, then the single one of those 30 days that best matches the model day in the local neighborhood (1x1° box) around the point being downscaled is identified. This multi-scale matching is one of the key aspects of LOCA, and ensures that the final downscaled field is consistent with the day being downscaled on both local and synoptic (weather-system) length scales.

The final downscaled value is the value from the best-matching single observed day, scaled so that its amplitude matches the model day being downscaled. For example, if the model gridcell has a 5°C temperature anomaly, but the best matching observed day shows only a 4°C anomaly when averaged over the model gridcell, then the value at the point being downscaled is increased by 1°C. Or, if the model gridcell experiences 0.50 inches of precipitation, but the best matching observed day shows 0.55 inches of precipitation, then the value at the point being downscaled is decreased by 10%.

Although the details of LOCA can become complicated, in large part because of rare cases or for computational efficiency, the essential simplicity of the scheme should be kept in mind. LOCA simply finds the best-matching 30 historical days in the region, then finds the single one of those days that best matches locally (in a 1x1° box around the point being downscaled), then scales the final value to be consistent with the model.

An example of the LOCA downscaling process is shown in Figure 5.

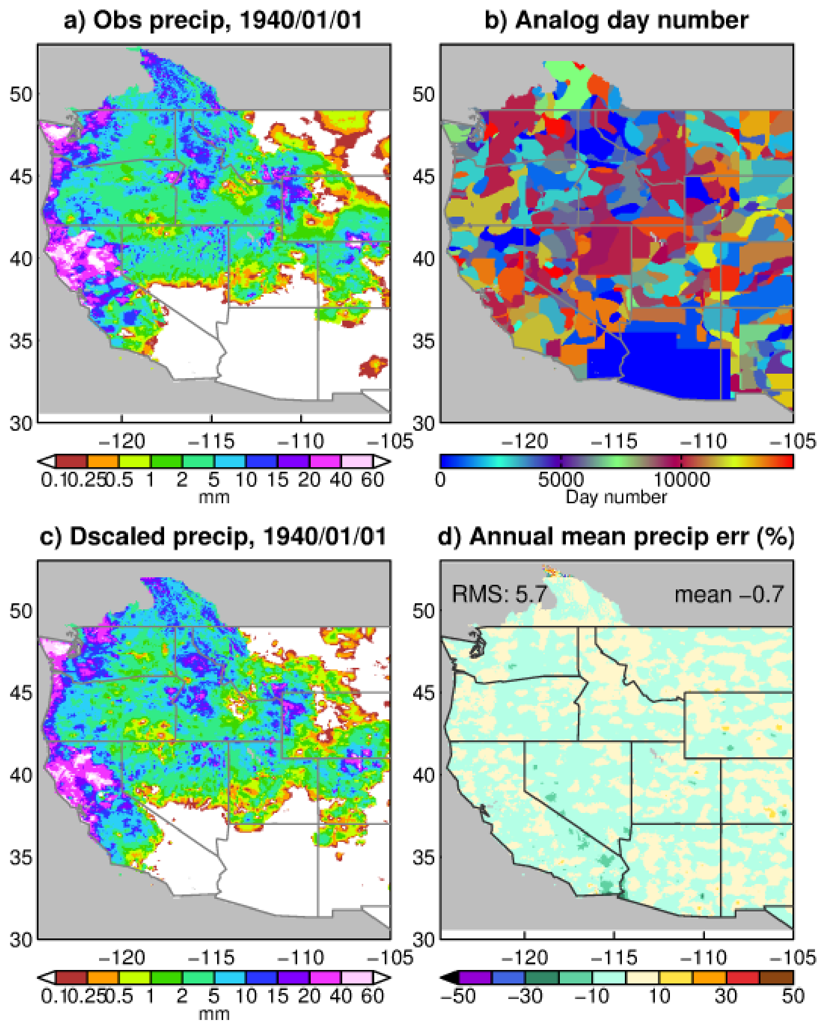

Figure 5. An example showing the LOCA process downscaling precipitation on Jan 1st, 1940. The observationsfor that day was first coarsened to a 1x1 degree latitude-longitude grid to simulate a typical GCM's resolution (not shown). This coarse-scale representation of the precipitation field was downscaled. The LOCA process was trained on data from 1970-2010, so this day being downscaled was not part of the training data. Panel a) shows the original fine-resolution (1/16th degree) precipitation on that day. Panel b) shows, at each location, the analog day number that the LOCA process selected. Day numbering starts at 1 for Jan 1st, 1950. Note that the selected analog day changes for each day, so this "jigsaw-puzzle" like pattern is different for every day being downscaled. Panel c) shows the final downscaled precipitation field after LOCA; it can be compared to panel a), the actual fine-resolution precipitation field. Panel d) shows the annual mean precipitation error (%). The mean error is -0.7%, with an RMS error of 5.7%.

One key goal when developing the LOCA downscaling process was to preserve, to a reasonable degree, daily extremes and variability. This goal was selected because the economic impacts of climate change are preferentially due to extreme events – heat waves, floods, droughts, and so on (Pierce, 2012). LOCA does a better job than the scheme used in previous California assessment reports at preserving variability because it averages the data less than previous schemes when constructing the final downscaled field. In LOCA, the single best matching analog day is chosen for downscaling, while in the previous scheme, the 30 best-matching analog days are used to form a weighted average. The averaging tends to reduce the simulated extremes. For example, Figure 6 shows the mean yearly maximum precipitation at each location from observations and after downscaling using LOCA and an earlier constructed analog downscaling method, BCCA.

Another aspect of the downscaled simulation that LOCA addresses is to accurately represent the observed spatial coherence in the downscaled precipitation field. If rainfall over two adjacent valleys always occurs simultaneously, then the downstream flows will tend to combine, increasing the chance of flooding. If the valleys tend to receive their rain independently, it is less likely that both valleys will

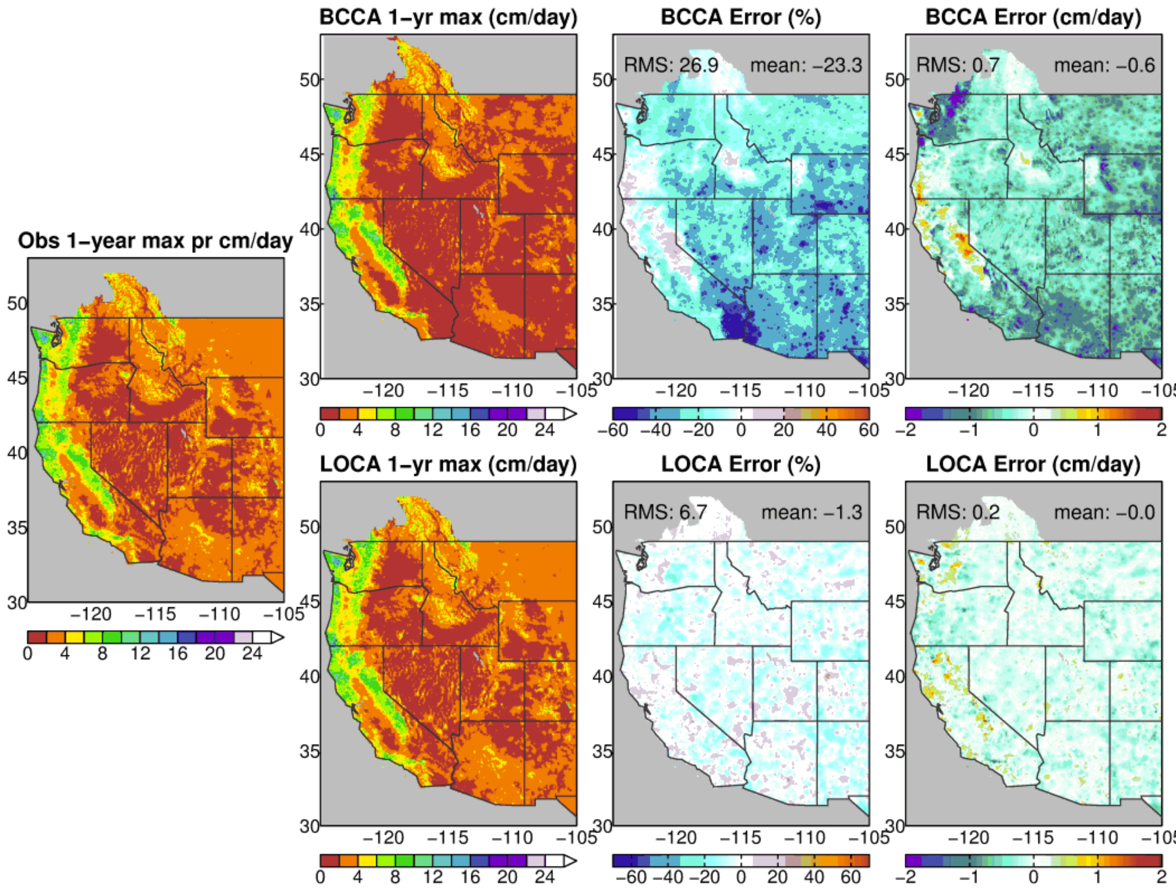

Figure 6. An illustration of downscaling extremes, showing the average maximum daily precipitation at each point in LOCA and an earlier constructed analog method, BCCA. The left panel shows the observed mean daily maximum precipitation (cm/day). The top panels show the same field using BCCA downscaling, and the error in BCCA in percent and cm/day. The lower panels show the same field using LOCA downscaling, and the error in LOCA in percent and cm/day. The mean BCCA error over the region shown is −23.3%, while it is only −1.3% in LOCA. The RMS error is 26.9% in BCCA, but only 6.7% in LOCA.

simultaneously experience substantial rainfall, with less chance of downstream flooding. Since downscaling starts with a GCM whose coarse grid can cover many valleys simultaneously, downscaling can result in too much simultaneous rain over adjacent valleys (too much spatial coherence), skewing the simulated flood statistics computed from the downscaled data.

How coherent the precipitation field is can be measured using various techniques. Although we do not go into detail here, one approach is to estimate how quickly mean precipitation drops as an ever larger number of valleys are included in the averaging. If the rainfall is too coherent, the mean will drop more slowly than it should. This is illustrated in Figure 7, which shows a measure of spatial coherence of the precipitation field across the continental U.S. after downscaling with three different methods. LOCA does the best at retaining the original pattern of spatial coherence in this evaluation.

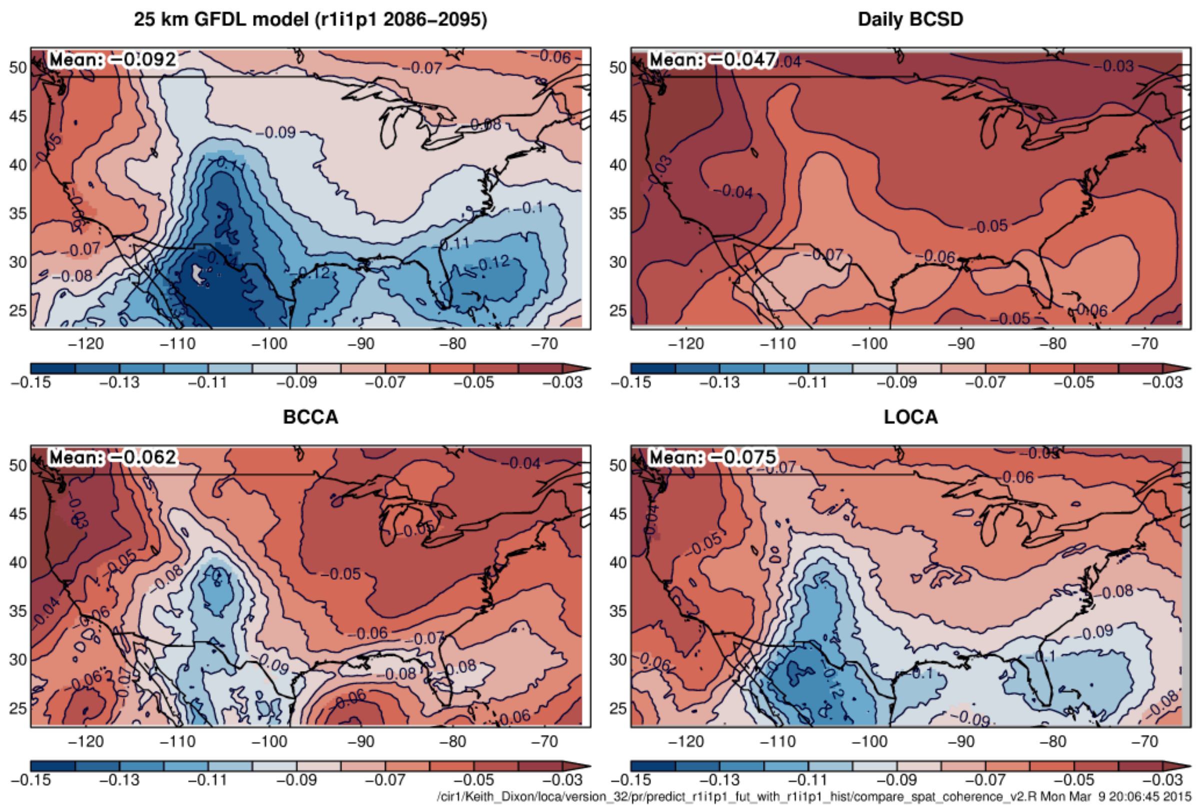

Figure 7. A measure of spatial coherence of the precipitation field over the continental United States. Red values show where where neighboring points are more likely to experience precipitation at the same time (i.e., where the field is more spatially coherent). Blue areas show where neighboring points are less likely to experience precipitation at the same time (i.e., less spatial coherence). Values are non-dimensional. Top left panel: The spatial coherence in a high resolution numerical model simulation at the end of this century (2086-2095), serving as a proxy for observations; this is the target that the downscaling is attempting to reproduce. Top right: The spatial coherence after downscaling using the daily BCSD method, which is commonly used for water resource studies. Lower left: Coherence after downscaling with BCCA, a method that has been used for previous California state climate assessments. Lower right: Coherence after downscaling with LOCA. The field after downscaling with LOCA (lower right) comes closest to reproducing the original spatial coherence (top left). The other methods increase the spatial coherence more than LOCA does.

5. The VIC land surface and hydrology model

Every GCM incorporates its own land surface model. However, modeled land surface characteristics and hydrology are highly sensitive to the spatial resolution of the model in regions with pronounced topography, such as found in California with the coastal range, Central Valley, and Sierra Nevada. With 32 GCMs using a variety of spatial resolutions, the GCMs are on a very unequal footing in representing key aspects of California's land surface. Additionally, the GCMs have a range of capabilities incorporated into their embedded land surface models, including some simplistic ones that neglect processes of importance for future climate impacts. Because of these issues, we do not directly use the output from the GCMs' land surface models.

To avoid these problems we use the LOCA-downscaled fields of daily precipitation and minimum and maximum temperature to drive a single land surface/hydrology model, the Variable Infiltration Capacity (VIC) model (Liang et al., 1996). VIC uses the high resolution (1/16th degree) LOCA precipitation and temperature to calculate rain, snow, snow cover, soil moisture content (in three layers), sublimation of water vapor from the surface, evaporation, transpiration (water loss) from plants, runoff, surface heat fluxes, and more. These variables are critical for some impact studies, such as those revolving around wildfire, agriculture, and ecosystems. Annual mean maps of some of the land surface variables simulated by VIC are shown in Figure 8. A full list of variables is given in Appendix 2.

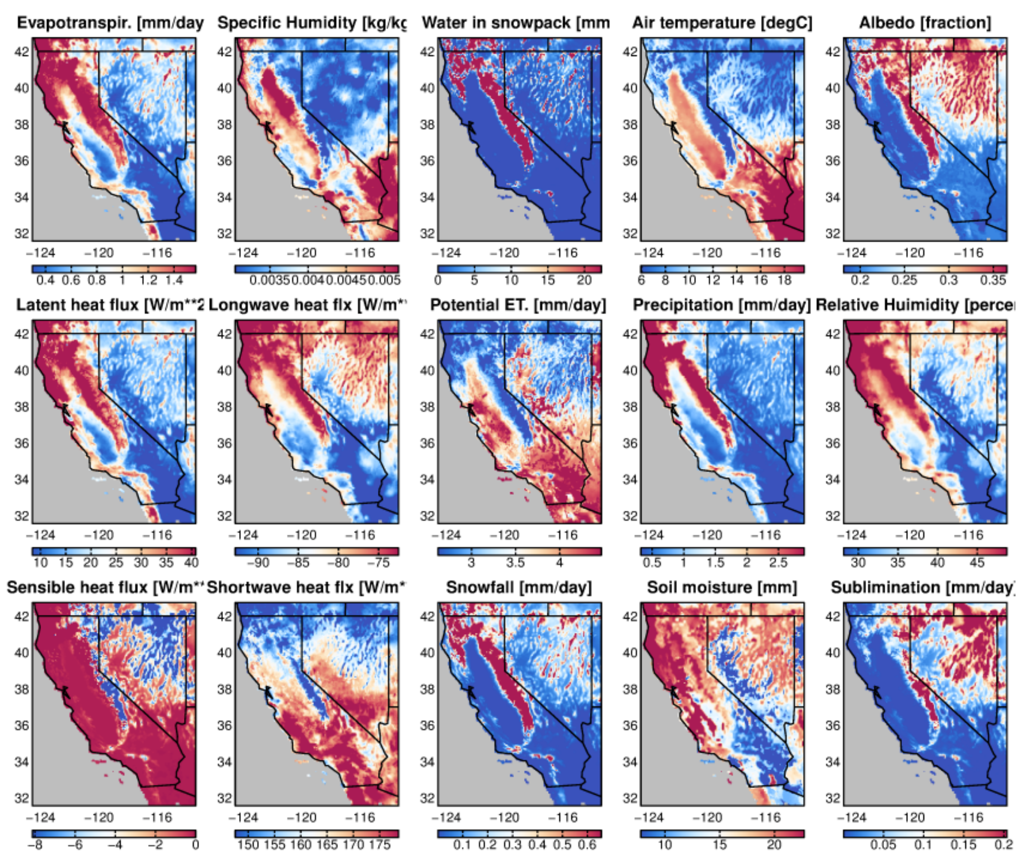

Figure 8. Annual average maps of some of the land surface and hydrology variables saved from the VIC model run. All variables are saved on the 16th degree latitude-longitude grid on a daily time step.

There are many different land surface models, and even when driven by the same LOCA-downscaled meteorological forcing they would give a spread of results. In other words, there is a degree of uncertainty added to projected climate variables when meteorological data is translated through a land surface model. Even though VIC is well regarded and widely used in the western U.S., there is more confidence in variables that are directly downscaled from the GCMs than variables extracted from a land surface model that is driven by downscaled meteorological fields.

Currently, the only variable that is both directly downscaled from the GCMs and computed by the land surface model is humidity. VIC estimates humidity from the difference between daily minimum and maximum temperature, among other factors, which is not as robust a method for estimating humidity as is downscaling humidity from the original GCM humidity fields. A project to downscale humidity using LOCA is presently in the early stages of development, to be completed in the next several months.

6. Choosing models for impact studies

The large amount of data produced in this effort, ultimately about 40 TB, can be unwieldy for some impact studies to manage. Although results from all 32 downscaled models, under two RCPs, can be used for the most comprehensive assessment and should be considered whenever possible, this may not always be practical. We have therefore developed suggestions for sensible subsets of the data to use that will give most of the benefits of using all 32 GCMs but at a significantly reduced data volume.

Model	Institution
ACCESS1-0	CSIRO (Commonwealth Scientific and Industrial Research Organization), Australia, and Bureau of Meteorology, Australia
CCSM4	The National Science Foundation, The Department of Energy, and the National Center for Atmospheric Research, United States
CESM1-BGC	The National Science Foundation, The Department of Energy, and the National Center for Atmospheric Research, United States
CMCC-CMS	Centro Euro-Mediterraneo per i Cambiamenti, Italy
CNRM-CM5	CNRM (Centre National de Recherches Meteorologiques, Meteo-France, Toulouse,France) and CERFACS (Centre Europeen de Recherches et de Formation Avancee en Calcul Scientifique, Toulouse, France
CanESM2	CCCma (Canadian Centre for Climate Modelling and Analysis, Victoria, BC, Canada)
GFDL-CM3	NOAA Geophysical Fluid Dynamics Laboratory, Princeton, N.J., USA
HadGEM2-CC	Met Office Hadley Centre, Fitzroy Road, Exeter, Devon, EX1 3PB, UK
HadGEM2-ES	Met Office Hadley Centre, Fitzroy Road, Exeter, Devon, EX1 3PB, UK
MIROC5	JAMSTEC (Japan Agency for Marine-Earth Science and Technology, Kanagawa, Japan), AORI (Atmosphere and Ocean Research Institute, The University of Tokyo, Chiba, Japan), and NIES (National Institute for Environmental Studies, Ibaraki, Japan)

Table 1. The 10 global climate models selected by the California Department of Water Resources CCTAG team as having a good simulation of California's climate.

A reasonable first step to reduce the number of models is to select a subset of models that perform better in simulating both global and California climate. We follow the recent California Department of Water Resources' effort in this area; their Climate Change Technical Advisory Group evaluated the full set of CMIP5 models to determine which did best in California. As described in their report (CA Dept. Water Resources Climate Change Technical Advisory Group 2015), various selection criteria were sequentially applied to winnow down the original set of CMIP5 GCMs. The criteria included: evaluating global climatology; evaluating western U.S. climate and hydrology; evaluating California state hydrology and climate extremes; and reducing the final set to a more manageable set of 10 GCMs. If the full set of 32 GCMs cannot be accommodated, a more tractable option would be to use the 10 CCTAG GCMs shown in Table 1.

Metric	Spatial weighting (on 1/16° grid)	Overall metric weight
Average summer daily maximum temperature	By log of population	0.35
Annual average precipitation volume	(Implicitly Northern California weighted, since wetter there)	0.30
Average winter daily maximum temperature	None	0.15
Dry spell intensity (lowest total precipitation in 10-yr period)	None	0.10
Variability of average summer daily maximum temperature	By log of population	0.033
Variability of annual average precipitation volume	(Implicitly Northern California weighted, since wetter there)	0.033
Variability of average winter daily maximum temperature	None	0.033

Table 2. Measures (metrics) of climate model projections used in this work. Values are averaged over the state of California on the LOCA 1/16th degree grid using the indicated spatial weighting. The final contribution of each metric to the overall rank of the model (i.e., each metric's overall importance) is shown in the third column ("Overall metric weight").

However, even a set of 10 GCMs may be too much data in some circumstances. Accordingly, we have identified 4 of the 10 GCMs from Table 1 that can be described as producing: 1) a "warm/dry" simulation; 2) an "average" simulation; 3) a "cooler/wetter" simulation; 4) the model simulation that is most unlike the first 3 (for the best coverage of different possibilities). The procedure for identifying these 4 simulations is as follows:

1. Identify measures (metrics) of model performance that are important for California climate impact studies. The seven measures we used, covering a broad spectrum of aspects of California climate including both temperature and precipitation measures, are shown in Table 2.
2. Rank (1-10) each model on each of the 7 metrics. So, for example, for the summer average daily maximum temperature metric, the warmest model is assigned a rank of 1 and the coldest model is assigned a 10.

3. Weight the metrics according to subjective criteria as to how important we consider each metric to be when evaluating California state climate impacts. The weight of each measure in the final tally is shown in the last column of Table 2 (values sum to 1). Overall, 50% of the weighting is given to temperature metrics, 40% to precipitation metrics, and 10% to variability (on the basis that greater climate variability is more difficult to adapt to). Summer temperature is spatially weighted by population since energy demand and health impacts of summer heat waves increase with temperature, while the precipitation metrics are implicitly weighted towards Northern California, since the majority of the state's precipitation falls in that region.

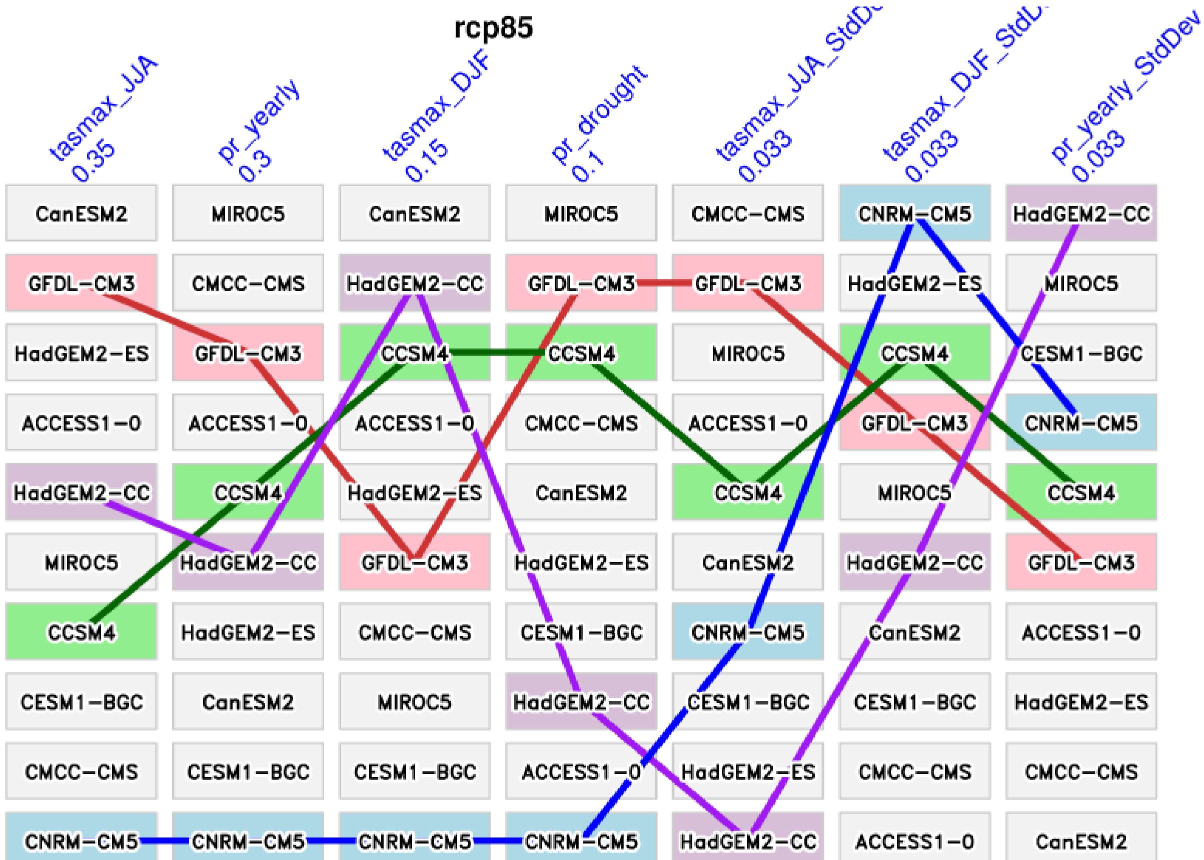

Figure 9. Choosing a subset of 4 models to represent the 10 GCMs that best simulate California's climate. Each column of grey boxes corresponds to one of the metrics of model performance indicated in Table 2. The highest box in each column is labeled with the model that has rank 1 in that metric, while the lowest box in each column is the model that has rank 10. For example, the leftmost column (labeled "tasmax_JJA / 0.35", for the summer [June-July-August] daily maximum temperature [tasmax] metric, which has a weighting of 0.35), shows that the CanESM2 model was the rank 1 (warmest) model on this metric, while CNRM-CM5 was the rank 10 (coolest) model on this metric. The model with the weighted rank closest to 1 across all metrics and both RCPs (4.5 and 8.5) is GFDL-CM3, as indicated in the red boxes; this is the "warm/dry" model. The model with the weighted rank closest to the average value across all metrics/RCPs is CCSM4, indicated by the green boxes; this is the "average" model. The model with the weighted rank closest to 10 is CNRM-CM5 (blue boxes); this is the "cool/wet" model. The final selected model, HadGCM2-CC (purple boxes), is the model that has the pattern of rankings that is most unlike GFDL-CM3, CCSM4, and CNRM-CM5, and is chosen to give better coverage of the full spread of model results. Temperature measures arranged from warmest (top) to coolest (bottom); precipitation measures ranked from lowest (top) to highest (bottom).

4. Compute the final weighted ranking of each model. We then choose the model with the smallest rank (the warm/dry model), the rank closest to the mean (the average model), the largest rank (the cool/wet model), and the model that, mathematically, is most unlike the previous 3 models in its rankings (Figure 9).

Two aspects of this procedure affect the results and should be noted. First, the period we used to evaluate performance was 2015-2050; using a different period would result in a somewhat different set of models being selected. Second, we computed the model average rankings across both the RCP 4.5 and 8.5 emissions scenarios together. The intent is that the final set of 4 models should be used in impact studies with both the RCP 4.5 and 8.5 scenarios. This was done to simplify the final recommendation, so that the suggested set of models for the RCP 4.5 scenario would be the same as the set for the RCP 8.5 scenario.

The final results of this process are shown in Figure 9 (only results from RCP 8.5 are shown, for brevity). The warm/dry model is GFDL-CM3, the average model is CCSM4, the cooler/wet model is CNRM-CM5, and the model most unlike those 3 is HadGEM2-CC.

Taking into account the results of this process, our recommendations for what models to use for California climate impact studies are as follows:

1. Results from all 32 GCMs and both RCP's (4.5 and 8.5) should be used if possible. This will give the best evaluation of climate change impacts taking into account the role of natural climate variability and accounting for systematic differences among climate models.
2. If all 32 GCMs cannot be used, then we recommend using the RCP 4.5 and 8.5 scenarios from the 10 models selected by the California DWR CCTAG for the quality of their simulation of California's climate (Table 1): ACCESS1-0, CCSM4, CESM1-BGC, CMCC-CMS, CNRM-CM5, CanESM2, GFDL-CM3, HadGEM2-CC, HadGEM2-ES, and MIROC5.
3. If using the 10 CCTAG models is impractical, we recommend using the RCP 4.5 and 8.5 scenarios from the following four models: GFDL-CM3, CCSM4, CNRM-CM5, and HadGEM2-CC.

From our experience and that of others studying climate projections, we do not recommend using less than 4 models for a climate change impacts evaluation. This is because natural climate variability, such as the El Nino/La Nina cycle, has a pronounced effect on California's climate. Using only one or two models may end up inadvertently evaluating the impacts of natural climate variability rather than the impacts of climate change. The more models that are used, the more that climate fluctuations due to natural climate variability are averaged away, exposing the consistent human-caused climate change signal (Pierce et al., 2009).

7. Extended Drought Scenario

California is susceptible to dry spells within its highly variable climate. A warming climate will compound drought impacts, as evidenced during recent precipitation deficits during the 2000's drought in the Southwest (Colorado River basin), and during the ongoing 2012-2015 drought in California and neighboring states. Furthermore, some recent research suggests that extended drought occurrence ("mega-drought") could become more pervasive in future decades (e.g. Cook et al. 2015). To investigate implications of drought, an extended drought scenario during the 21st Century will be constructed for California—this work is in its planning stages, and will become a focus topic later this year. Multiple inputs will be used to develop this scenario, including observed dry spell characteristics from the instrumental period, evidence concerning the amplitude and duration of drought from Holocene-period paleo-climate information (e.g. tree rings and other measures), and using meteorological and hydrological information from dry spells within 21st Century climate projections from selected GCMs. The objective is to produce an observationally-grounded, several year (~20year) drought scenario during the next several decades whose climate has warmed significantly over historical climatology. Because drought scenarios are an active topic in California and Nevada, we have established a working relationship with other groups who are developing drought scenarios for the Russian River and for the eastern Sierra/western Nevada, in order to develop consistent, unified scenarios, to the extent possible.

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Appendix 1. Global Climate Models (GCMs) used in this work

Model	Institution
ACCESS1-0	CSIRO (Commonwealth Scientific and Industrial Research Organization), Australia, and Bureau of Meteorology, Australia
ACCESS1-3	CSIRO (Commonwealth Scientific and Industrial Research Organization), Australia, and Bureau of Meteorology, Australia
CCSM4	The National Science Foundation, The Department of Energy, and the National Center for Atmospheric Research, United States
CESM1-BGC	The National Science Foundation, The Department of Energy, and the National Center for Atmospheric Research, United States
CESM1-CAM5	The National Science Foundation, The Department of Energy, and the National Center for Atmospheric Research, United States
CMCC-CM	Centro Euro-Mediterraneo per i Cambiamenti, Italy
CMCC-CMS	Centro Euro-Mediterraneo per i Cambiamenti, Italy
CNRM-CM5	CNRM (Centre National de Recherches Meteorologiques, Meteo-France, Toulouse,France) and CERFACS (Centre Europeen de Recherches et de Formation Avancee en Calcul Scientifique, Toulouse, France
CSIRO-Mk3-6-0	Australian Commonwealth Scientific and Industrial Research Organization (CSIRO) Marine and Atmospheric Research (Melbourne, Australia) in collaboration with the Queensland Climate Change Centre of Excellence (QCCCE) (Brisbane, Australia)
CanESM2	CCCma (Canadian Centre for Climate Modelling and Analysis, Victoria, BC, Canada)
EC-EARTH	EC-Earth (European Earth System Model)
FGOALS-g2	IAP (Institute of Atmospheric Physics, Chinese Academy of Sciences, Beijing, China) and THU (Tsinghua University)
GFDL-CM3	NOAA Geophysical Fluid Dynamics Laboratory, Princeton, N.J., USA
GFDL-ESM2G	NOAA Geophysical Fluid Dynamics Laboratory, Princeton, N.J., USA
GFDL-ESM2M	NOAA Geophysical Fluid Dynamics Laboratory, Princeton, N.J., USA
GISS-E2-H	NASA/GISS (Goddard Institute for Space Studies) New York, NY, USA
GISS-E2-R	NASA/GISS (Goddard Institute for Space Studies) New York, NY, USA
HadGEM2-AO	NIMR (National Institute of Meteorological Research, Seoul, South Korea) in association with the Met Office Hadley Centre, UK
HadGEM2-CC	Met Office Hadley Centre, Fitzroy Road, Exeter, Devon, EX1 3PB, UK
HadGEM2-ES	Met Office Hadley Centre, Fitzroy Road, Exeter, Devon, EX1 3PB, UK
IPSL-CM5A-LR	Institut Pierre Simon Laplace, Paris, France
IPSL-CM5A-MR	Institut Pierre Simon Laplace, Paris, France
MIROC-ESM-CHEM	JAMSTEC (Japan Agency for Marine-Earth Science and Technology, Kanagawa, Japan), AORI (Atmosphere and Ocean Research Institute, The University of Tokyo, Chiba, Japan), and NIES (National Institute for Environmental Studies, Ibaraki, Japan)
MIROC-ESM	JAMSTEC (Japan Agency for Marine-Earth Science and Technology, Kanagawa, Japan), AORI (Atmosphere and Ocean Research Institute, The University of Tokyo, Chiba, Japan), and NIES (National Institute for Environmental Studies, Ibaraki, Japan)
MIROC5	JAMSTEC (Japan Agency for Marine-Earth Science and Technology, Kanagawa, Japan), AORI (Atmosphere and Ocean Research Institute, The University of Tokyo, Chiba, Japan), and NIES (National Institute for Environmental Studies, Ibaraki,

	Japan)
MPI-ESM-LR	Max Planck Institute for Meteorology, Hamburg, Germany
MPI-ESM-MR	Max Planck Institute for Meteorology, Hamburg, Germany
MRI-CGCM3	MRI (Meteorological Research Institute, Tsukuba, Japan)
NorESM1-M	Norwegian Climate Centre, Norway
bcc-csm1-1-m	Beijing Climate Center(BCC),China Meteorological Administration, China
bcc-csm1-1	Beijing Climate Center(BCC),China Meteorological Administration, China
inmcm4	INM (Institute for Numerical Mathematics, Moscow, Russia)

Appendix 2. Available Variables

The following table shows the variables available, and whether they are downscaled from the GCMs or derived from VIC.

All variables are daily average, unless noted.

Name	Units	[V]IC or [G]CM?
Daily maximum temperature (2 m above surf) (instantaneous)	degC	G
Daily minimum temperature (2 m above surf) (instantaneous)	degC	G
Precipitation	mm/day	G
Evapotranspiration	mm/day	V
Runoff	mm/day	V
Soil moisture (3 layers)	mm	V
SWE (water content of snow)	mm	V
Daily change in SWE	mm/day	V
Snowfall rate	mm/day	V
Rainfall rate	mm/day	V
Snow melt rate	mm/day	V
Dew rate	mm/day	V
Sensible heat flux	W/m**2	V
Latent heat flux	W/m**2	V
Potential evapotranspiration (PET) from vegetation	mm/day	V
Air temperature (2 m daily average)	degC	V
Relative humidity (2 m above surface)	percent	G, V
Specific humidity (2 m above surface)	kg/kg	G, V
Albedo (surface reflectivity)	fraction	V
Shortwave down	W/m**2	V
Shortwave net	W/m**2	V
Longwave net	W/m**2	V
Sublimation net	mm/day	V
Windspeed (10 m above surface)	m/sec	G