Climate Model Selection for the Reclamation Central Valley Project (CVP) Long-Term Operation Study

Drew Allan Loney, PhD PE, Bureau of Reclamation, Lakewood, CO, dloney@usbr.gov
Michael Wright, PhD PE, Bureau of Reclamation, Lakewood, CO, mwright@usbr.gov
Kunxuan Wang, PhD PE, Bureau of Reclamation, Lakewood, CO, kwang@usbr.gov
Kevin Thielen, PhD PE, Bureau of Reclamation, Lakewood, CO, kthielen@usbr.gov
Derya Sumer, PhD PE, Bureau of Reclamation, Lakewood, CO, dsumer@usbr.gov

Abstract

In 2021, the Bureau of Reclamation (Reclamation) and the California Department of Water Resources (DWR) jointly requested Reinitiation of Consultation on the Coordinated Long-Term Operation of the Federal Central Valley Project (CVP) and the State Water Project (SWP), henceforth referred to as the 2021 LTO. The motivation for the reinitiation was the extensive Western drought that required further analysis beyond the 2019 LTO to determine appropriate operations under the drier and warmer conditions.

Extensive and ongoing work on climate change in California has shown that warming temperatures and changing weather regimes are likely to have a significant impact on CVP/SWP water resources. To describe future system management under these potential future conditions, it is necessary to incorporate projections of future climate effects within the LTO analysis. It is also prudent to incorporate climate change into the analysis in such a way that recognizes the inherent uncertainty associated with climate projections in order to plan for a broad range of potential future CVP/SWP operational conditions.

The overall goal of this climate analysis is to inform the development of inputs necessary for water operations, temperature, and temperature dependent fish morality (TDM) models which comprise the core 2021 LTO analysis. This requires determining climate scenarios that are likely representative of future climate conditions within California. Consistent with many of the previous efforts mentioned above, this determination is made by evaluating the accuracy of the general circulation models (GCMs) over the historical period in comparison to observationally informed datasets such as the Parameter-elevation Regressions on Independent Slopes Model (PRISM). Though good historical performance is not necessarily an indicator of future performance, notably poor performance in the historical period calls into question the reliability of a GCM for predicting future conditions.

The climate analysis is founded on a joint Reclamation/DWR understanding of climate change science relevant to California water management. The analysis builds upon previous climate work, incorporating lessons learned from previous studies and improved best practices. This work is representative of current knowledge and data; future efforts should continue to build upon the present analysis to further refine understanding of climate effects within California.

Introduction

The Reclamation Central Valley Project (CVP) extends four hundred miles north to south across the heart of California, consisting of six major storage facilities and numerous other smaller facilities as shown in Figure 1 (Maven's Notebook, n.d.). Although the facilities are cooperatively managed for multiple purposes, the primary goals of the project are water delivery and environmental compliance. The CVP is managed in conjunction with the California State Water Project (SWP) which, together with smaller locally managed facilities, jointly regulate flows within the California basin. The CVP/SWP operate based on regulatory guidance developed from an understanding of the California basin hydrology. When hydrologic conditions shift significantly to impact CVP/SWP operations, Reclamation initiates a consultation process with State and other stakeholder groups to formulate new operational guidance. Given the ongoing drought through the American West and generally warming trends, Reclamation initiated a consultation in 2021, referred to here as the 2021 LTO for brevity.

Figure 1. Map of the Reclamation Central Valley Project.

Understanding how climate change will impact hydrology is critical for understanding future CVP operations. Climate change is anticipated to impact operations both through hydrologic changes as well as repartitioning the available water among different uses. Hydrologic shifts will alter allocations based on total available water, storage, melt timing, evaporation, and increased consumptive uses. Meteorologic and hydrologic changes may require reallocation of water away from human uses toward environmental compliance with instream flow and temperature targets. The magnitude and timing of climate change driven shifts dictate when and the extent to which CVP operations will need to adapt to the new conditions. It is therefore important to estimate the magnitude and timing of climatic changes to account for them within the 2021 LTO.

However, the timing and magnitude of hydrologic shifts under climate change are highly uncertain. While this is in many respects driven by the realized greenhouse gas concentrations, it is also a function of the inherent uncertainty of climate feedback mechanisms and the ability of the scientific community to describe their interaction. It is therefore necessary to develop an approach that recognizes the most likely outcome as well as the range of potential outcomes and, in that process, removes scenarios that are known to be infeasible. Often referred to as model culling, selection, or subsetting, model selection maintains only those estimates that are credibly representative of future conditions (Raju & Kumar, 2020). The method offered in the present work is one selection approach focused specifically on water resources applications. Although the approach generalizes across basins, the analysis centers on generating a credible climate change model ensemble subset of future CVP conditions.

Methods

Consistent with previous work in California – such as the California Department of Water Resources (DWR) Climate Change Technical Advisory Group's (CCTAG) "Perspectives and Guidance for Climate Change Analysis" (Lynn et al., 2015), the Water Storage Investment Program (WSIP) (California State Water Resources Control Board, 2022), and the Delta Conveyance Project (DCP) (California Department of Water Resources, 2022), and Reclamation's SECURE Water Act Report 2021 (Bureau of Reclamation, 2021) – this analysis makes use of General Circulation Models (GCMs) from the Coupled Model Intercomparison Project 5 (CMIP5) used in the fifth assessment report of the United Nations Intergovernmental Panel on Climate Change (IPCC) (World Climate Research Program, 2020). The CMIP5 GCM ensemble consists of multiple models which each provide simulations over a historical period (1950-2005) as well as simulations of future conditions under a number Representative Concentration Pathways (RCPs), often referred to as emissions scenarios. As with the previous work mentioned above, this study considered two RCPs for high and low emissions. CMIP5 accounts for numerical model uncertainty, in considering the GCM ensemble, and the emissions uncertainty, in the two RCP pathways. A limitation of the approach, and that of the CMIP5 dataset, is an uncharacterized degree of uncertainty from the initial condition and meteorological forcing assumptions (Lehner et al., 2020).

Past efforts have typically evaluated the raw GCM output or applied simplistic corrections to said output. However, to apply GCM output for water resources planning, the course spatial grid of the GCMs must be "down-scaled" to provide input data on operational spatial scales. In contrast with previous methodologies, the work here evaluates the performance of the CMIP5 models after downscaling. There are many methods of downscaling GCM data, the choice of which itself introduces additional uncertainty. The downscaling method used in this work is the Locally

Constructed Analog (LOCA) Method of Pierce et al, 2015 which has been used in Reclamation's 2021 SECURE Water Act Report to Congress and is considered the state-of-practice (Pierce et al., 2015).

The present analysis can thus be seen as an extension of previous approaches with new methods and metrics intended to better describe the skill of the GCMs and the paired downscaling methods. Skill evaluation with GCM ensemble subsetting is necessary due to the variability in GCM numerical implementations as well as the LOCA downscaling and bias correction. Depending on the GCM numerical implementation, the model formulation may be more or less skillful at capturing the California climate. Without removal from the ensemble, an unskillful model may distort future climate estimates which would carry through the modeling workflow to result in unrealistic CVP operations. Evaluation after downscaling assesses the joint performance of the GCM/downscaling as the downscaling operation can significantly alter the GCM characteristics. While this approach neglects characterizing if a GCM numerical implementation is appropriate for California, it would capture any performance degradation caused by an improper numerical formulation.

The resulting GCM ensemble subset uses the performance of the GCMs over the historical reanalysis period as a proxy for being credibly representative of future climate conditions. Downscaled GCM performance was evaluated using metrics of temporal skill, spatial skill, and interannual variability over the historical period. Poor performing GCMs based on historical temperature and precipitation skill were removed from the GCM ensemble for predicting future conditions. All comparisons were made to the 800m Parameter-elevation Regressions on Independent Slopes Mode (PRISM) dataset over the historical period (*PRISM Climate Group, Oregon State University*, 2020). Although temperature was evaluated within the framework, subsetting was not done on any temperature metric as performance was substantially similar among the ensemble members. Evaluation was done over the California HUC2 basin, which comprises all of the California Central Valley (U.S. Geologic Survey, 2022).

Temporal

Temporal skill is intended to highlight any systematic annual error in the downscaled GCMs across the historical period. The mean annual precipitation and difference from PRISM is shown in Figure 2. No GCM performs meaningfully worse on average than the ensemble due to the bias correction performed bythe LOCA downscaling. No GCMs were therefore eliminated based on temporal performance.

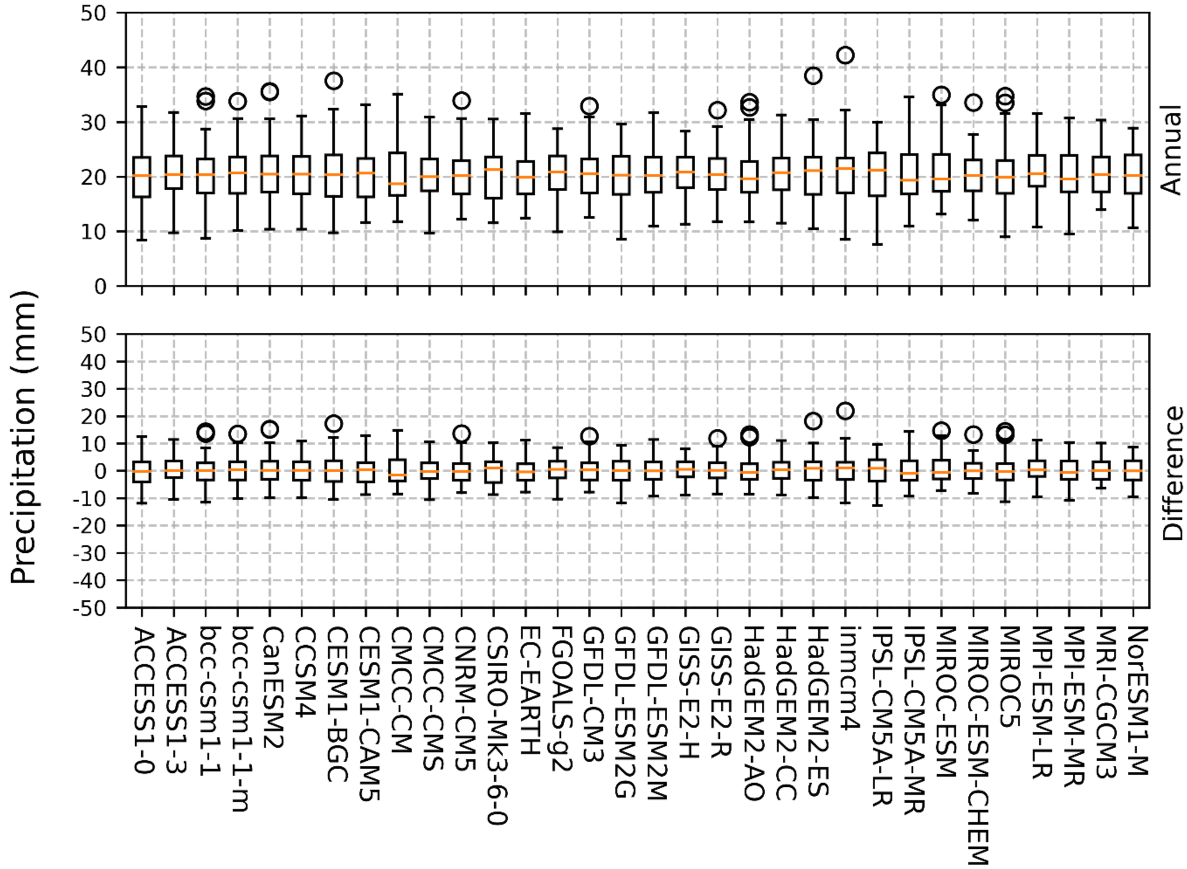

Figure 2. Mean average error of the GCMs across the Central Valley over the historical reanalysis period. The centerline represents the median, the range of the bar is the 25th/75th quartiles, and the whiskers extend beyond the box by 1.5 times the interquartile range.

Spatial

Spatial skill is intended to evaluate any systematic bias in where the downscaled GCMs place precipitation across California. This is of particular concern because, even if there is no temporal bias, changes to the spatial precipitation distribution from north or south or east to west can significantly alter CVP/SWP operations. As the dominant precipitation mechanism in California is atmospheric rivers, the zonal (north-to-south) distribution of precipitation is the primary precipitation metric.

Spatial skill was evaluated by a Kolmogorov-Smirnov test on the north to south placement of longitudinally averaged zonal precipitation. Figure 3 gives the score for each GCM. As with the temporal analysis, skill across the GCMs was similar due to the bias correction and no GCMs were eliminated based on this metric.

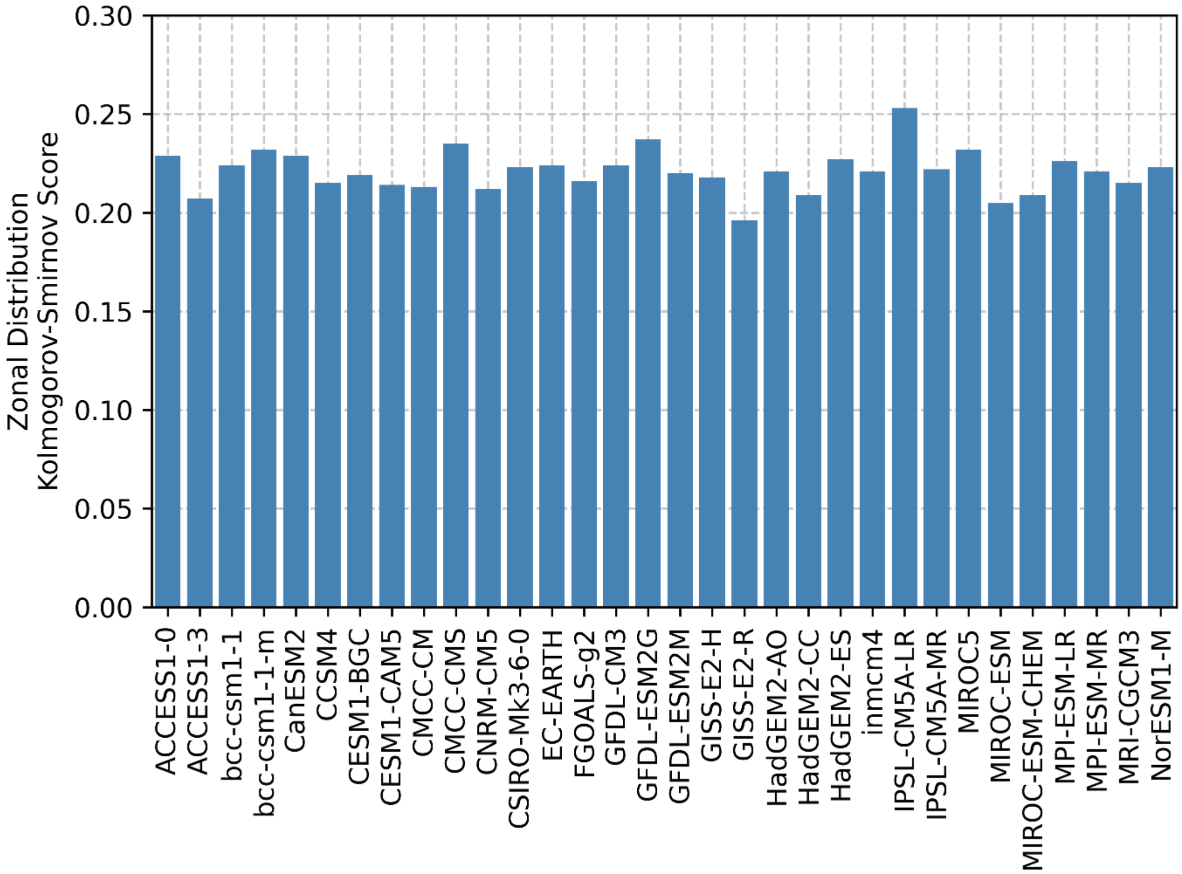

Figure 3. Kolmogorov-Smirnov score for the zonal precipitation distribution across the Central Valley over the historical reanalysis period.

Interannual variability

Interannual variability describes the transition through wet/dry cycles typical of California. The magnitude of the cycle as well as its periodicity are key criteria for water management. Evaluation of interannual variability was separated into two components – continuous magnitudes and categorical water year typing – to highlight different behavior within the GCMs.

Continuous water year precipitation magnitudes were evaluated against the PRISM dataset using a Kolmogorov-Smirnov test. This tests that the overall frequency of precipitation magnitudes is similar between the GCMs and PRISM, scores of which are given in Figure 4. GCMs performing more than one standard deviation worse than the mean score were eliminated from the GCM ensemble.

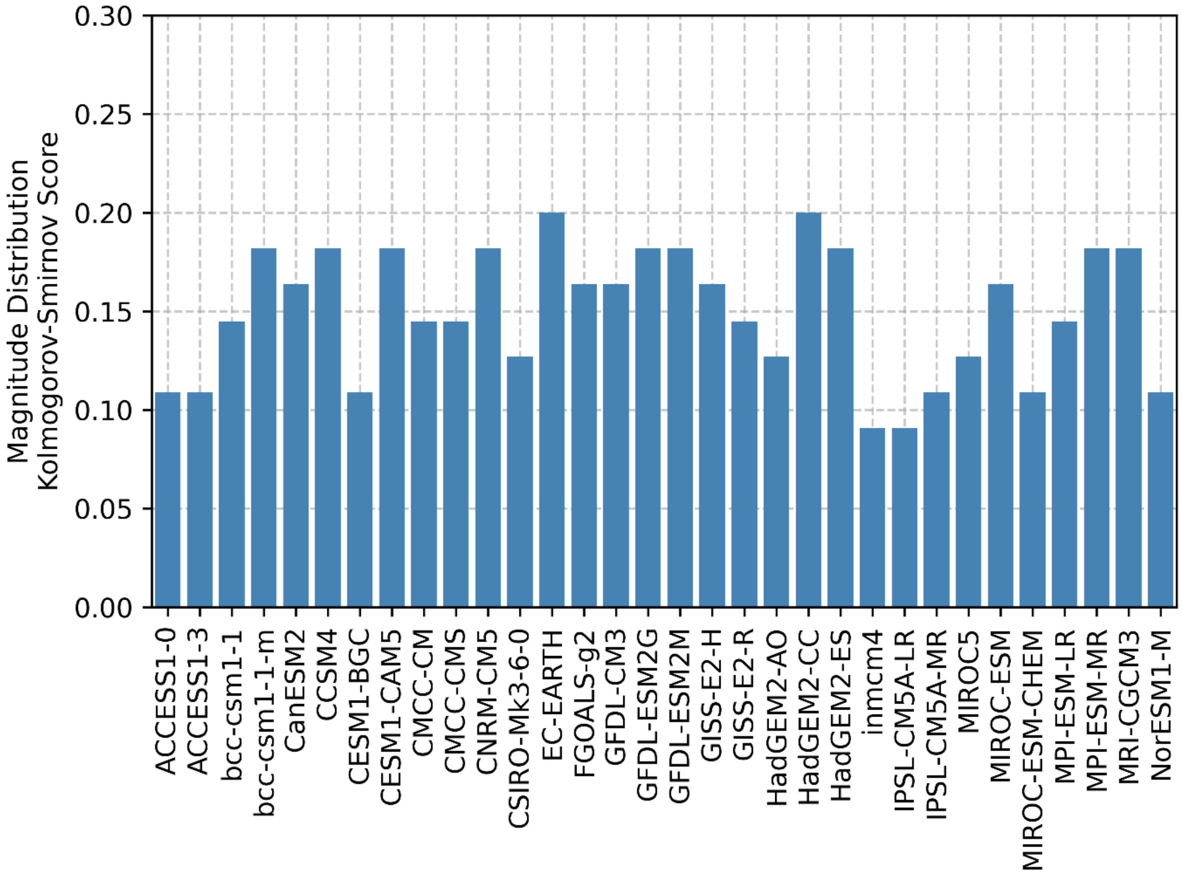

Figure 4. Kolmogorov-Smirnov score for the mean precipitation magnitude distribution across the Central Valley over the historical reanalysis period.

Categorical evaluation was done by defining water year types based on percentiles referenced to the PRISM record. The percentiles were taken as given in Table 1. The magnitudes from the PRISM percentiles were applied to the GCMs to evaluate the transition rate between the water year types within each GCM as well as the mean average error of each water year type within the GCM. The PRISM percentiles were maintained to evaluate the water year types within the GCMs. Transition rates were ordered as a continuous distribution and evaluated using a Kolmogorov-Smirnov test, the values of which are given in Figure 5. GCMs performing more than one standard deviation worse than the mean score were again eliminated. Any GCMs having greater than 10% magnitude error for any individual water year type were also eliminated. These two criteria ensure the frequency of the transitions as well as the magnitudes are consistent between the GCM and the historical record.

Results

The GCM subset retained 20 of the 32 CMIP5 LOCA downscaled GCMs that had reasonable performance over the historical period. These members included the five original members from the CCTAG selection. A list of the remaining GCMs is given in Table 2. Removal of the historically worst performing GCMs over California increases confidence that the remaining subset of GCMs are likely to be representative of future conditions in the region under climate change.

Table 1. Percentile thresholds within the PRISM dataset used to establish water year types

Year Type	Percentile Range	
	Lower	Upper
Critical Dry	--	10%
Dry	10%	25%
Below Normal	25%	50%
Above Normal	50%	75%
Wet	75%	--

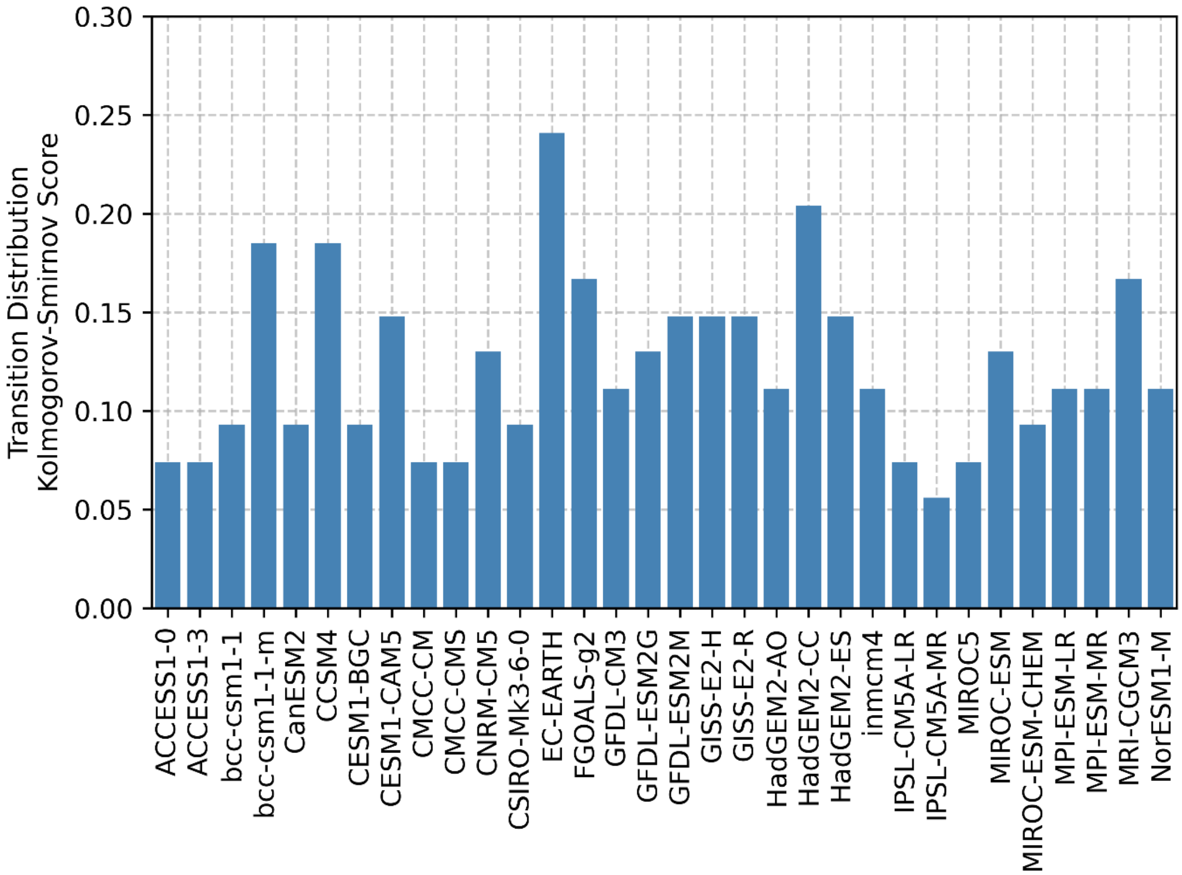

Figure 5. Kolmogorov-Smirnov score for the water year transition distribution across the Central Valley over the historical reanalysis period.

The two RCPs from each of the 20 selected GCMs form an ensemble of 40 climate projections which describe the range of future climate conditions in California. Because future emissions are not known, the high and low RCP are considered equally likely. The range of these 40 climate projections is due to the uncertainty in the climatological response to greenhouse gas emissions as well as limitations in physical process representations of the GCMs. In order to address this uncertainty, it is necessary to incorporate multiple climate scenarios into the LTO analysis. Multiple climate scenarios allow the 2021 LTO to account for both the climate and modeling uncertainty by looking across range of likely variability bounded by the GCMs.

Table 2. CMIP5 ensemble members with selection and justification for exclusion

General Circulation Model	Excluded	Justification
ACCESS1-0	No	
ACCESS1-3	No	
bcc-csm1-1	No	
bcc-csm1-1-m	Yes	Transition probability
CanESM2	Yes	Dry bin magnitude
CCSM4	Yes	Transition probability
CESM1-BGC	No	
CESM1-CAM5	No	
CMCC-CM	No	
CMCC-CMS	Yes	Critical dry bin magnitude
CNRM-CM5	No	
CSIRO-Mk3-6-0	No	
EC-EARTH	Yes	Transition score
FGOALS-g2	Yes	Critical dry bin magnitude; transition score
GFDL-CM3	Yes	Critical dry bin magnitude
GFDL-ESM2G	No	
GFDL-ESM2M	No	
GISS-E2-H	No	
GISS-E2-R	No	
HadGEM2-AO	No	
HadGEM2-CC	Yes	Dry bin magnitude; transition score
HadGEM2-ES	No	
inmcm4	No	
IPSL-CM5A-LR	Yes	Critical dry bin magnitude
IPSL-CM5A-MR	No	
MIROC5	No	
MIROC-ESM	Yes	Multiple bin magnitudes
MIROC-ESM-CHEM	Yes	Multiple bin magnitudes
MPI-ESM-LR	No	
MPI-ESM-MR	No	
MRI-CGCM3	Yes	Transition score
NorESM1-M	No	

Figures 6 and 7 show the median precipitation and streamflow variability in future conditions for the Eight River Index which reflects locations that are relevant to the CVP/SWP water management. The streamflow is estimated by averaging the VIC routed GCM ensemble at each location (Lawrence Livermore National Laboratory, 2014). The 2021 LTO focuses on the 2040 climate condition; values are reported as an average around that year. Overall, the median future precipitation of all 40 projections is slightly more wet than the historical average while the future streamflow is slightly drier. The large increase in precipitation July through September is from a relatively small base. This is potentially indicative of greater atmospheric moisture capacity at higher temperatures, greater losses due to evapotranspiration, and a shift to runoff earlier in the year due to earlier snowmelt as well as a transition from solid to liquid precipitation.

To represent the range of future variability within the 2021 LTO, the GCM subset will be used to construct six climate scenarios referenced to the ensemble variability. A median value in temperature and precipitation from the GCM ensemble represents the most likely future climate and will serve as the primary decision scenario. Additionally, combinations of the 25^{th} and 75^{th} precipitation and temperature changes give hot/dry, hot/wet, warm/dry, and warm/wet scenarios to describe the bounds of likely future climate change sensitivity. Finally, an extreme hot/dry case will be developed that combines the 95^{th} temperature percentile with the 5^{th} percentile precipitation as a stress test scenario for the maximum reasonable impact as predicted by the GCM ensemble variability.

Each of these six climate scenarios are used as inputs for a Variable Infiltration Capacity (VIC) hydrologic model based on the historical California hydrology. Temperature and precipitation deviations are calculated for 30-year periods centered on 1995 and 2040 for the historic and future conditions, respectively. The future temperature and precipitation are mapped back to the VIC inputs by creating a quantile map relationship between the historic and future condition for each VIC grid cell. Although this approach decouples the VIC input from the physical processes represented within a single GCM, it recognizes the overall variability of the GCM ensemble and that the ensemble is more likely to predict the variability than any individual GCM alone. The VIC meteorology and outputs are used to create inflows to CalSim 3 and forcings for the remaining 2021 LTO models.

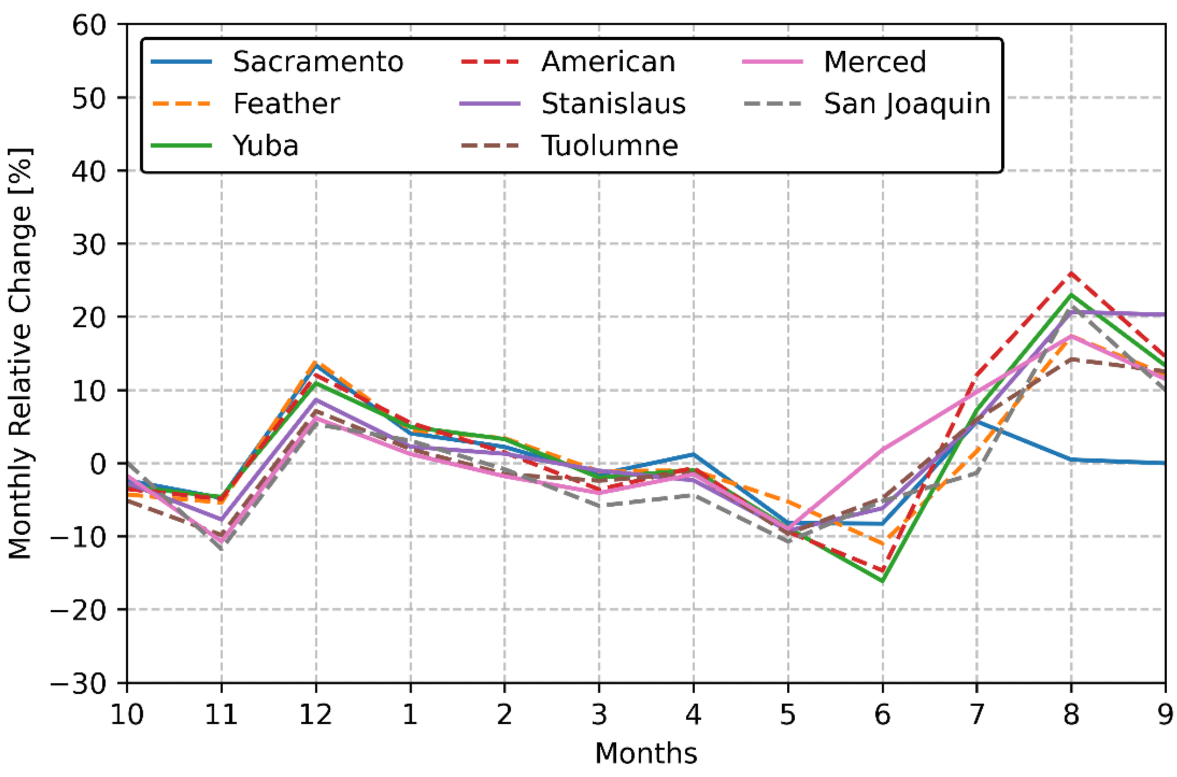

Figure 6. Median relative precipitation change in the catchments above the Eight River Index locations, referenced from 1980-2010 and 2025-2055 within the 2021 40 climate projection ensemble

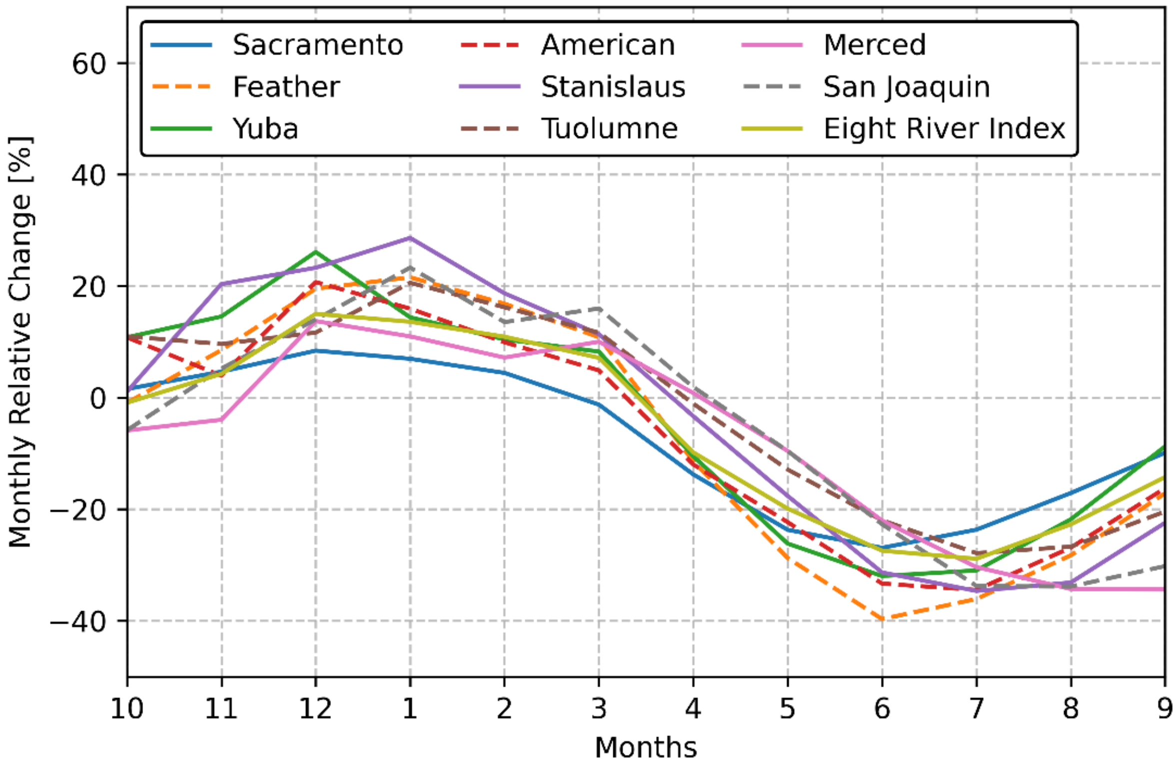

Figure 7. Median relative runoff change in the Eight River Index locations, referenced from 1980-2010 and 2025-2055 within the 2021 40 climate projection ensemble. An average of the prerouted GCM values was utilized (Lawrence Livermore National Laboratory, 2014).

Conclusions

The 2021 LTO analysis incorporates the state-of-practice in assessing climate change for water resources applications, building upon lessons learned in previous regional studies. Given the long-term trends identified across the region, it is prudent for Reclamation and CA DWR to incorporate climate change effects when evaluating future CVP/SWP operations. While the specific shifts due to climate change are highly uncertain and will only be clear once realized, the approach developed for the 2021 LTO represents a credible estimate for the likely conditions 2040 with sensitivity around that estimate.

It should be noted that intra-annual variability was not used as a selection mechanism given limitations in the CMIP5 ensemble. Intra-annual variability characterizes seasonal shifts – such as seasonal precipitation timing or seasonal temperatures – that would provide greater fidelity on annual climatic patterns. While these can be readily calculated from the GCMs, seasonal patterns remain sensitive to the assumed initial conditions and meteorological forcings. Because the CMIP5 ensemble is a single initial condition and forcing dataset across the members, seasonality is likely only partially characterized. It is hoped that the CMIP6 dataset, which has multiple forcing conditions for several of the GCMs, may be better suited to evaluate seasonality as a selection mechanism.

The developed approach is a generalized means to evaluate the representativeness of GCMs for water resources applications. For basins less driven by the north-to-south precipitation distribution, an additional spatial metric can be introduced to evaluate longitude performance. In particular, evaluation of interannual variability provides a much-needed water resources metric beyond the suite commonly utilized within the atmospheric modeling community. However, the current analysis represents a snapshot in both climate understanding and data that should continue to be revised in future work as both continue to grow. As CMIP6 data becomes available with revised downscaling techniques, the approach should be adapted to that GCM ensemble to maintain the best available climate data in water resources.

References

Bureau of Reclamation. (2021). *Water Reliability in the West—2021 SECURE Water Act Report* (p. 60). Department of the Interior.

California Department of Water Resources. (2022, December 14). *Delta Conveyance*. https://water.ca.gov/Programs/State-Water-Project/Delta-Conveyance

California State Water Resources Control Board. (2022, December 7). *Water Storage Investment Program (WSIP)*. https://www.waterboards.ca.gov/waterrights/water_issues/programs/wsip/

Lawrence Livermore National Laboratory. (2014, July 9). *Downscaled CMIP3 and CMIP5 Climate and Hydrology Projections*. https://gdo-dcp.ucllnl.org/downscaled_cmip_projections/#Welcome

Lehner, F., Deser, C., Maher, N., Marotzke, J., Fischer, E. M., Brunner, L., Knutti, R., & Hawkins, E. (2020). Partitioning climate projection uncertainty with multiple large ensembles and CMIP5/6. *Earth System Dynamics*, *11*(2), 491–508. https://doi.org/10.5194/esd-11-491-2020

Lynn, E., Chair, C., O'Daly, W., Keeley, F., Dsiwm, D., Woled, J., & Dsiwm, D. (2015). *Perspectives and Guidance for Climate Change Analysis* (p. 142). California Department of Water Resources.

Maven's Notebook. (n.d.). *Maps and Diagrams*. Maven's Notebook. Retrieved December 27, 2022, from https://mavensnotebook.com/resource-pages/maps-and-diagrams/

Pierce, D. W., Cayan, D. R., Maurer, E. P., Abatzoglou, J. T., & Hegewisch, K. C. (2015). Improved Bias Correction Techniques for Hydrological Simulations of Climate Change*. *Journal of Hydrometeorology*, *16*(6), 2421–2442. https://doi.org/10.1175/JHM-D-14-0236.1

PRISM Climate Group, Oregon State University. (2020). http://www.prism.oregonstate.edu/

Raju, K. S., & Kumar, D. N. (2020). Review of approaches for selection and ensembling of GCMs. *Journal of Water and Climate Change*, *11*(3), 577–599. https://doi.org/10.2166/wcc.2020.128

U.S. Geologic Survey. (2022, February 9). *Hydrologic Unit Maps*. https://water.usgs.gov/GIS/huc.html

World Climate Research Program. (2020, February 10). *CMIP Phase 5 (CMIP5)*. https://www.wcrp-climate.org/wgcm-cmip/wgcm-cmip5