Memorandum on LOCA2-Hybrid Downscaling

Interim Deliverable for EPC-20-006,

Prepared by: David W. Pierce, Daniel R. Cayan, Peter Yao, Stefan Rahimi, Julie Kalansky,
Scripps Institution of Oceanography, UCSD & UCLA

December 2025

- This research is funded by the California Energy Commission (CEC) through its Electric Program Investment Charge (EPIC) Program, which invests in scientific and technological research to accelerate the transformation of the electricity sector to meet the state's energy and climate goals.
- The applied research grant, EPC-20-006, will integrate the latest downscaling approaches applied to the recently produced global climate models (GCMs) with an engagement process to develop a robust, usable, set of climate projections applicable for California.
- This memo is being shared to support transparent and timely consideration of interim deliverables that are relevant for energy stakeholders and all those interested in California's next generation of climate projections.

This memorandum is submitted to the CEC by UC San Diego's Scripps Institution of Oceanography. The memo meets deliverable requirements under Task 5 of the California Energy Commission's applied research grant EPC-20-006: Hybrid LOCA Downscaling

OVERVIEW

This report describes the LOCA version 2 Hybrid downscaling (LOCA2-Hybrid) process developed as part of this project agreement: EPC-20-006. Drawing upon selected short reports posted on the Climate Data and Analysis Working Group (C-DAWG) website (https://www.energy.ca.gov/programs-and-topics/topics/research-and-development/climate-data-and-analysis-working-group-c-dawg), this summary document includes a description of the LOCA2-Hybrid version of the Localized Constructed Analogs (LOCA) statistical method, which was used to downscale Global Climate and Earth System Models for the California energy community and for California's Fifth Climate Change Assessment. This report describes important elements that span the set of project deliverables. Included in the description are the variables that are downscaled, the LOCA2 training data and the bias correction process, the hybrid downscaling method, the CMIP6 models that were downscaled including SSPs and ensemble members. This report also presents selected results from the LOCA2-Hybrid downscaled projections, including a small sampler of comparative plots showing LOCA2-Hybrid CMIP6 downscaled outcomes against results using the traditionally used historical data base training methodology supplied by LOCA2 CONUS downscaling (which was not developed as part of this research).

LOCA DOWNSCALING

The Localized Constructed Analogs (LOCA) statistical downscaling method (Pierce et al. 2014; Pierce et al. 2015a; Pierce et al. 2015b) is an analog based method that is used to downscale relatively coarse scale global climate model projections to finer scale regional projections. In conducting this global to regional downscaling, LOCA uses sets of observationally-based training data over the regional domain for two purposes: 1) bias correction; 2) to provide a library of observed weather patterns that, after spatial coarsening, are matched to the global climate model (GCM) day being downscaled. We call the latter the "pattern library".

The LOCA downscaling method proceeds in two steps: 1) firstly, a coarser scale downscaling from the original GCM grid (which varies by GCM) to a common 0.5 x 0.5 degree grid. 2) secondly, a high resolution downscaling from the common 0.5 degree grid to the final, fine scale 3 km grid. The step is used so that all models can be bias corrected using information from the same 0.5 degree grid, even though the GCMs have different grid resolutions (Pierce et al. 2014). This initial downscaling is applied to the target variable to be downscaled; and it is confined to the downscaling domain rather than the entire global domain. Other schemes sometimes interpolate, an analysis confined to and constrained by the parent global model result, rather than additionally incorporating observationally-based bias reduction as does the initial downscaling operation. Our analysis has found that the interpolation can lead to a poorer representation of spatial variability in the final downscaled result.

All versions of the Localized Constructed Analogs (LOCA) statistical downscaling method use training data in the spatial downscaling processes, but also in the bias correction. The training data is a set of multi-decade observational or observationally-guided data. Since LOCA is designed to reproduce the statistics (e.g., seasonal variation, seasonal averages, etc.) of the training data in the final historical portion of the downscaled result, the training data plays a key role in the downscaling process and determines the climatology, annual cycle, and variability of the downscaled result.

As noted, this version of LOCA employs "hybrid" downscaling (Pierce et al. 2023c), which advances from the more familiar version of LOCA that is sometimes referred to as LOCA1, described in Pierce et al. 2018. LOCA1 was used in California's Fourth Climate Change Assessment, the Fourth National Climate Assessment (NCA4), and a close offshoot was used in the recent Fifth National Climate Assessment (NCA5). LOCA1 relies upon gridded historical observed training data in developing analog patterns for future climate. New components implemented in the LOCA2-Hybrid downscaling are a dynamically downscaled reanalysis and dynamically downscaled global climate model projections as input to different phases of the LOCA statistical downscaling. Using a library of dynamically downscaled patterns from future projections avoids the stationarity limitation imposed when historical observations form the analogs from which future downscaled values are developed. Both of these dynamical modeled components are conducted using the Weather Research and Forecasting (WRF) regional dynamical model (Skamarock, et al, 2019).

BIAS CORRECTION

Global climate models use millions of calculations and estimations to represent interactions in the earth system. This information and data are extremely useful for understanding the climate system and predicting its future change. However, all models have errors. Systematic model errors are called biases. Examples of climate model biases include overly wet winters or heat waves that are not as extreme as observed. The process of reducing model biases is called *bias correction*. There are many different kinds of model biases and numerous bias correction methods. Because of this, descriptions of bias correction can be confusing to users of the climate scenarios data, since different methods with different goals and outcomes are used.

Biases tend to be complicated functions of time of year and how extreme the value is. For example, temperature biases may be different in winter than summer due to model errors in depicting snow processes, or precipitation biases may be different on "average" wet days than extreme wet days due to how atmospheric rivers are simulated. Accordingly, bias correction methods often are applied by month or season, and sometimes consider how the bias changes as values become more extreme (e.g., Panofsky and Brier, 1968; Thrasher et al., 2012).

Being a hybrid product, the LOCA2-Hybrid downscaling incorporates uncertainties in the original GCM-WRF data (Rahimi-Esfarjani 2022a and 2022b), since LOCA2 assumes that the pattern library is a faithful depiction of the spatial patterns of weather variability seen in reality. The GCM-WRF runs were bias corrected (Pierce et al. 2023a) before use in the pattern library since WRF (like all models) has biases it its output, so the attendant uncertainties that apply when bias correction is used apply here as well. The standard LOCA bias correction scheme is used, which preserves GCM-predicted trends in variables by quantile (Pierce et al. 2015a).

Both the LOCA2 and WRF products start with the global climate model (GCM) projections produced by various groups around the world. GCMs typically have large biases. For example, a GCM that simulates twice as much winter precipitation as observed in California is not uncommon. The LOCA2-Hybrid runs apply bias correction to the GCM values using the PresRat

(Pierce et al. 2015) method before the downscaling step. PresRat computes the bias correction by season and how extreme the value is.

All LOCA2-Hybrid runs apply a seasonal bias correction after the downscaling step to preserve the match between the projected results and observations. Historically this has been termed "post downscaling bias correction". Different kinds of WRF downscaled GCM model run results have been produced (Rahimi 2022a, 2022b), some with *a priori* bias correction, some with both *a priori* and *a posteriori* bias correction, and an initial set of runs with no bias correction. However, the four projections with *a priori* bias correction were not yet available when the LOCA2-Hybrid training data (described below) were being developed, so they were not employed in the LOCA2-Hybrid work flow.

TRAINING DATA

As mentioned above, the LOCA 3km California region downscaling supported under EPC-20-006 by the California Energy Commission introduced a new set of analogue training datasets that were generated by atmospheric models, albeit guided by observations. Constructing the LOCA2-Hybrid training data begins with the ERA5[1] reanalysis (Hersbach et al. 2020), a state-of-the-art global atmospheric reanalysis at ~30 km spatial resolution that incorporates a large volume of weather observations in its generation. The ERA5 reanalysis is then dynamically downscaled by WRF to the 3 km spatial resolution used by LOCA2 (Pierce et al. 2023b). Even though ERA5 ingests large quantities of observations, both ERA5 and WRF, like all models, have biases that need to be corrected before the ERA5-WRF data can be used to train LOCA2. We therefore use daily station observations to bias correct the ERA5-WRF data. For temperature and precipitation, the bulk of the data is from GHCN-daily, only including stations with at least 30 years of valid data. For precipitation, 14 Eastern Sierra precipitation stations obtained from the Los Angeles Department of Water and Power (LADWP) are also included. To bias correct wind an assortment of observations was employed, including San Diego Gas and Electric station data, a collection of airport station observations, and RAWS stations obtained from colleague Tim Brown, Desert Research Institute, and observations from 10 available buoys off the coast of California. Humidity was corrected to GRIDMET observational analysis, which itself is a blended station/reanalysis product that has been put on a grid.

At each station and for each of the 12 months we calculate the difference between the station-observed value and the value from ERA5-WRF. We calculate these differences for all integer percentiles of the data from 1 to 99. Then for each combination of month and percentile we construct, over the California domain, a best-fit surface of the ERA5-WRF errors using the Generic Mapping Tools (GMT) "surface" function (Wessel et al. 2019). This surface yields an estimate of the ERA5-WRF bias at all locations, for each month-of-year and percentile. The bias is then removed arithmetically for temperature (and other non-positive definite variables) or multiplicatively for precipitation (and other positive definite variables). This methodology is similar to that used in Brown et al. 2016, although WRF-based interpolation between stations is not used in that work. We refer to the final bias corrected training data as ERA5-WRF-BC.

[1] ERA 5 is the fifth generation European Center for Medium-Range Weather Forecasts (ECMWF) atmospheric reanalysis of the global climate covering the period from Jan 1940 to present.

Downward surface solar radiation is the exception to this process. Our evaluations of WRF showed that coastal clouds are poorly represented in the ERA5-WRF simulations. Since these clouds have a strong bearing on rooftop solar photovoltaic electricity generation, we deemed the WRF data unsuitable for use as this variable's training data. We instead used GOES satellite observations as the basis for the surface downward solar radiation training data (Clemesha et al. 2016).

We evaluated the ability of our methodology to estimate precipitation in unobserved locations using a cross-validation method. Twenty stations that have many decades of daily observations and cover a range of climate conditions across California were selected for analysis. For each station, we first constructed an entirely new gridded station data set using the Livneh nearest-neighbor methodology (Livneh et al. 2015) but leaving out the station in question. We then compared the estimated time series at the omitted station's location to the actual time series from the station. We then repeated the process for the 20 cross-validation stations using the ERA5-WRF data, performing the complete surface-fitting bias correction process but again omitting the station in question. This process could only be done for precipitation since that was the variable we had the facilities to process due to the work in Pierce et al. 2021. Nonetheless, this is a reasonable evaluation of the methodology since precipitation has characteristics that present challenges for estimation, being heavily influenced by topography, covering a wide dynamic range across the landscape, and in some locations being locally patchy.

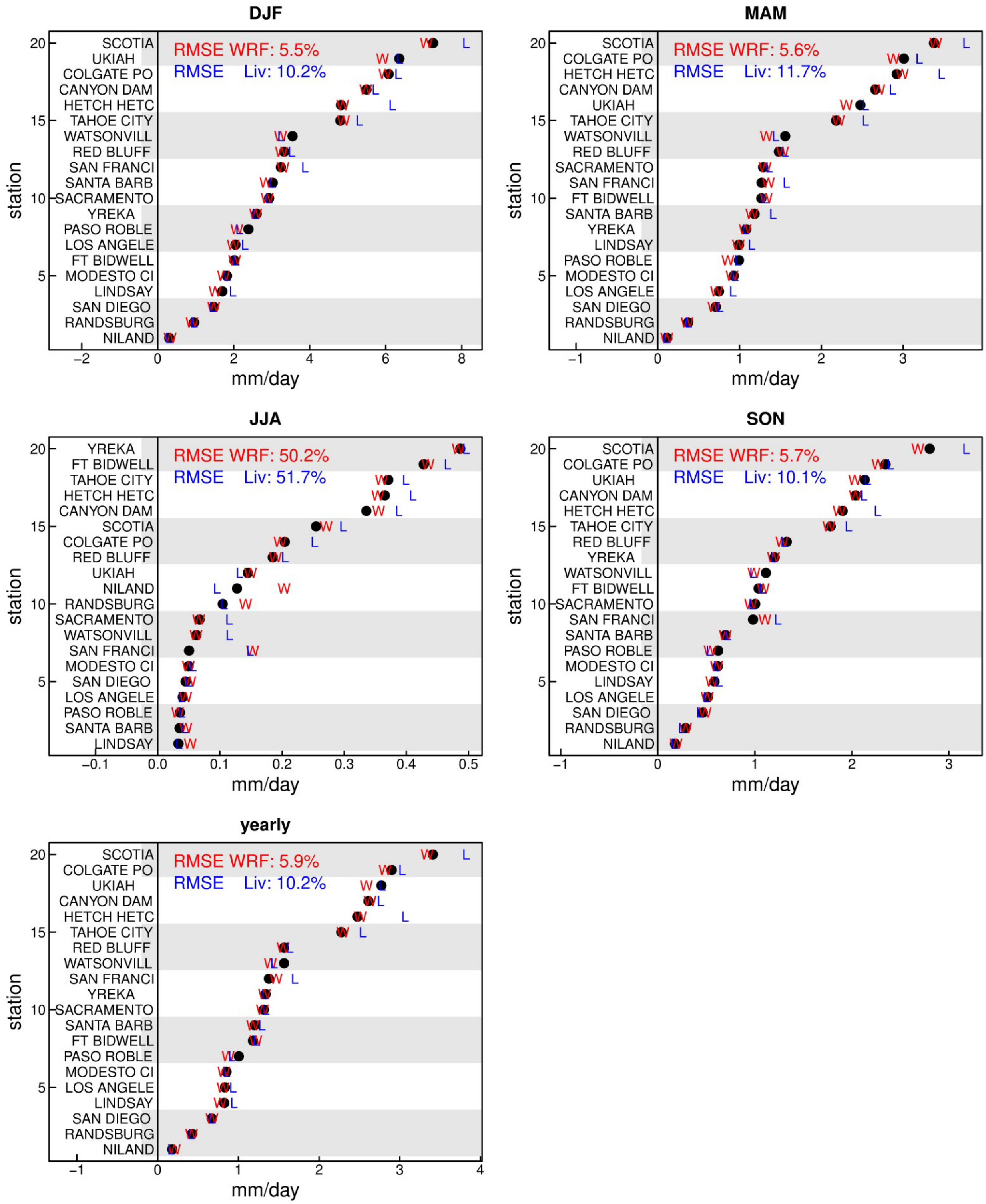

Figure 1. Mean daily precipitation by season at the 20 cross-validation stations from the original station observations (black dots), cross-validated Livneh results (blue L), and cross-validated WRF results (red W). In each panel stations are sorted from wettest to driest. The indicated RMSE values are calculated as percent errors across the 20 stations.

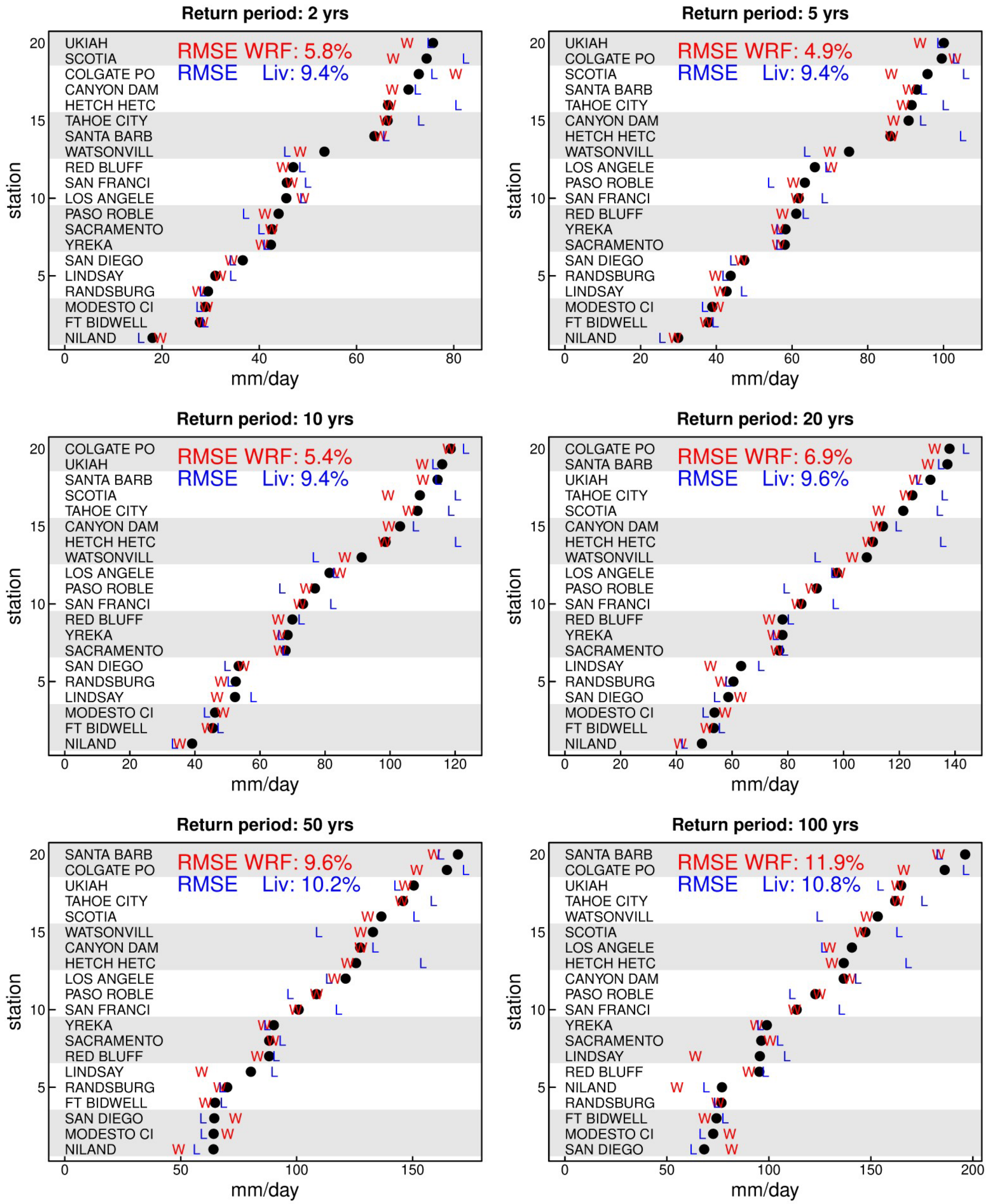

Figure 2. Return values (mm/day) of daily precipitation from the 20 cross-validated stations for different return periods from 2 to 100 years. Values from the original station data are shown as black dots, cross-validated Livneh values as the blue L, and cross-validated WRF results as the red W. The indicated RMSE values are calculated as percent errors across the 20 stations.

Results from the cross-validated analysis show that the Livneh gridded nearest-neighbor methodology is superior to ERA5-WRF-BC for capturing the specific day-by-day evolution of historically observed precipitation, presumably because neighboring stations are likely to experience precipitation at the same time as the omitted station. By contrast ERA5-WRF-BC produces precipitation via simulated processes that are close to, but not perfectly synchronized with observed precipitation on any given day. Therefore, if one wishes to know whether precipitation fell on some particular day (for example, for forensic meteorology applications), the nearest-neighbor re-gridding is preferable. On the other hand, over longer periods, errors in daily ERA5-WRF-BC tend to cancel out – **Figure 1** shows that the RMS error in yearly mean precipitation in cross-validated ERA5-WRF-BC is 5.9% across the 20 stations, about half the error seen in the cross-validated Livneh style nearest-neighbor interpolation (10.2%). Similar results are seen in winter (DJF), spring (MAM), and autumn (SON). Errors in summer are large in both methods (~20%) but the dry summer conditions in California make the summer evaluation of little interest compared to the performance in seasons when precipitation occurs. ERA5-WRF-BC likewise outperforms the nearest-neighbor method for extreme precipitation values (**Figure 2**), specifically for daily precipitation return periods between 2 and 20 years. By 50 years the difference in RMSE between the two methods falls to only about 1 percentage point.

PATTERN LIBRARY

The pattern library, which is a primary piece of the training data, plays an integral role in deriving LOCA downscaled results. In traditional LOCA, one library of historical weather patterns is used for two functions:

1. to bias correct the model across all times, from 1950-2100
2. to supply a library of weather patterns to use as analog days in constructing the downscaled fields

This traditional process was applied in California's Fourth Climate Change Assessment (Pierce et al. 2018) and the Fourth National Climate Assessment (NCA4) downscaling CMIP5 GCMs, along with the recent LOCA2 CONUS production used by the Firth National Climate Change Assessment (NCA5), downscaling a CMIP6[2] GCMs. The training data in that work were based on station observations interpolated to a regular grid using a form of nearest neighbor interpolation, then imposed on a specified monthly gridded climatology (Livneh et al., 2015; Livneh hereafter). The exception to this is the surface downward solar radiation training data, which was obtained from GOES satellite observations. Temperature was additionally corrected for elevation using a fixed lapse rate. Although this methodology has been used for decades to construct gridded data sets, it has some drawbacks. In particular, interpolating scattered station observations across regions of varied topography, such as found in California, may yield errors since the local topography at an unobserved location does not figure into the final result except insofar as the assumed gridded climatology reflects topography. The gridded climatology itself is an estimate since station observations in many regions are not available at the fine spatial resolution used for downscaling. In sum, the final gridded result supplies estimates of meteorological variables at unobserved locations that are informed by the values at neighboring stations, the elevation, and the estimated climatology.

[2] Climate Model Intercomparison Project versions 5 and 6

Using gridded historical observations for the pattern library is a reasonable approach and also a necessary one given that future observed weather patterns are not available. However, it does lead to some concerns. In particular, the warmer future climate will have less snow, possibly leading to altered surface temperature patterns in locations where snow is systematically lost in coming decades.

To address this concern of non-stationarity, in the LOCA version 2 (LOCA2 hereafter) California domain we used a hybrid downscaling scheme with a pattern library obtained from dynamically downscaled CMIP6 GCM Weather Research Forecasting (WRF; (Skamarock et al. 2019)) runs that were bias corrected to the ERA5-WRF-BC[3] training data (Pierce et al. 2023a). The period covered by the GCM-WRF runs extends to the year 2100, so a model estimate of future weather patterns can be obtained by this approach. This method is a form of hybrid downscaling since it couples the statistical downscaling approach of LOCA with a pattern library obtained from a dynamically downscaled model containing information about the historical and future climate. Thus, in moving forward from the traditional LOCA approach, in the California hybrid approach these two functions are disconnected. ERA5-WRF-BC is used for function #1, bias correcting the model, while WRF output is used for #2, to supply a library of contemporaneous weather patterns to construct the analog days in each period. So, both the ERA5-WRF-BC data (function #1) and the future WRF-CMIP6 data (function #2) are used, but for different purposes.

Regarding the pattern library, at the time when the WRF-CMIP6 simulations were being selected for pattern library usage, only *non*-a priori bias corrected simulations were available, so all of the WRF simulations fell into the *non*-a priori bias corrected category. For the LOCA2 California downscaling, the hybrid approach was implemented using UCLA's[4] WRF downscaled runs CESM2 r11i1p1f1 and EC-Earth3-Veg r1i1p1f1. These were run (like all the UCLA WRF simulations for this project) under emissions scenario SSP 370. The particular GCM-WRF runs were selected because Krantz et al. 2021 show that these two GCMs perform well in simulating historical climate variables over the California domain of interest here. In addition, the smaller memory requirements of the common 0.5 degree grid used in the first step of the LOCA process allow us to increase the membership of the pattern library by using results from the other two *non*-bias corrected models in the first half of the downscaling. Thus, in this initial step we used CNRM-ESM2-1 r1i1p1f2 and FGOALS-g2 r1i1p1f1 in addition to CESM2 r11i1p1f1 and EC-Earth3-Veg r1i1p1f1

LOCA2-Hybrid downscaling is split into 3 future periods so that the process can fit into the memory of the NASA Pleiades supercomputer where the runs were performed. In LOCA2 we used the standard CMIP6 historical period ending year of 2014, and three future periods of 2015-2044, 2045-2074, and 2075-2100. The pattern library for each of these three periods was obtained from the contemporaneous GCM-WRF downscaled (and bias corrected) run (i.e., when LOCA2-Hybrid downscaling was processing years 2075-2100 the pattern library was taken from

[3] ERA5-WRF-BC refers to the bias corrected (BC) dataset produced from application of WRF to downscale the ERA5 reanalysis. ERA5 is the fifth generation European Center for Medium-Range Weather Forecasts (ECMWF) atmospheric reanalysis of the global climate covering the period from January 1940 to the present.

[5] https://www.energy.ca.gov/sites/default/files/2024-09/e_Memo_2ndSet_WRF_runs_BC_Sept2024.pdf

WRF years 2075-2100, and similarly for the other periods). This means that end-of-century GCM days were downscaled using a pattern library from WRF simulation days also at the end of the century, and therefore will include any WRF-simulated changes in weather patterns in that time frame.

Thus, the WRF-CMIP6 projections employed in the LOCA2-Hybrid downscaling were taken from a subset of WRF downscaled CMIP6 Global Climate Models (GCMs) generated over the California region as part of this project (EPC-20-006). Computational limitations prevented running WRF high spatial resolution dynamical downscaling to dozens more GCMs, but the smaller subset provided a set of dynamically downscaled outcomes through the 21st Century that were employed in this hybrid downscaling production. The dynamical downscaling entailed embedding WRF across the California region to focus its computer power in a way that allowed for high-resolution topography (3-km grid length, and 40 vertical levels), coastlines, and small-scale features in the overlying weather and climate to be resolved. GCMs were dynamically downscaled to 45 km, then to 9 km, and then 3km (Figs 1,2), so each of the models that have a 3-km domain also has a 45-km and 9-km domain. All WRF downscaled simulations use the SSP 370 Shared Socioeconomic Pathway (SSP3)[5], covering the 1980-2100 time period. A total of 9 WRF simulations that were created for the 3km CMIP6 projection dataset over California were broken into two groups; an initial 4 non-a priori bias corrected simulations, and a second set of a priori bias corrected simulations. The 4 non-bias corrected GCM simulations are the simulations employed in the hybrid downscaling operation discussed here. Importantly, the WRF-CMIP6 data was bias corrected before using it in the pattern library. A downscaled reanalysis (ERA5) from 1980-2020 was also developed and bias corrected to evaluate biases in the dynamical downscaling methodology for both sets of downscaled GCMs.

LOCA2-Hybrid PROJECTIONS

Given the methodology and the training data described above, LOCA2-Hybrid downscaling was applied to a selected set of CMIP6 model projections (Pierce et al., 2023c). As described in https://loca.ucsd.edu/loca-version-2-for-california-ca-may-2023/, 15 models were included, chosen based on good performance over California as evaluated in Krantz et al. (2021): The LOCA2 downscaled CMIP6 models are ACCESS-CM2, CESM2-LENS, CNRM-ESM2-1, EC-Earth3, EC-Earth3-Veg, FGOALS-g3, GFDL-ESM4, HadGEM3-GC31-LL, INM-CM5-0, IPSL-CM6A-LR, KACE-1-0-G, MIROC6, MPI-ESM1-2-HR, MRI-ESM2-0, and TaiESM1. SSP 245, SSP 370, and SSP 585 are included, but only if the original GCM provided this scenario. A varied number (from 1 to 10) ensemble members were downscaled for the set of GCMs. Models for which 10 ensemble members were downscaled included CESM2-LENS, IPSL-CM6A-LR, and MPI-ESM1-2-HR.

COMPARISON: HISTORICAL CLIMATOLOGIES LOCA2-HYBRID vs LOCA2 CONUS

[5] The IPCC Sixth Assessment Report (2021) defines global emissions scenarios in terms of an SSP (Shared Socio-Economic Pathways) framework. Each SSP represents a scenario corresponding to projected socioeconomic global changes through 2100.

The training data is integral to LOCA downscaling because it provides the basis for bias correcting the GCM and WRF dynamical model components to the ultimate downscaled projection. As such, statistics of the historical portion of the training data determines the climatology of the historical portion of the downscaled output, which becomes the basis for determination of future changes depicted in the projection.

Constructing the climatological training data for LOCA2-Hybrid downscaling begins with the ERA5 reanalysis (Hersbach et al., 2020), a state-of-the-art global atmospheric reanalysis at ~30 km spatial resolution that incorporates a large volume of weather observations in its generation. The ERA5 reanalysis is then dynamically downscaled by WRF to the 3 km spatial resolution used by LOCA2. This methodology contrasts with the recent statistically downscaling conducted over the continental United States and adjacent parts of Canada and Mexico, which here is called LOCA2. CONUS The LOCA2 CONUS productions employed the advanced multi-model bias correction introduced in LOCA2-Hybrid downscaling, LOCA2 CONUS does not employ a hybrid numerical modeled training dataset, instead taking the standard LOCA1 approach in using historical data for its analog library. Specifically, similar to that used for California's Fourth Climate Change Assessment and the 4th National Climate Change Assessment, the present CMIP6 generation LOCA2 CONUS2 temperature and precipitation training library consists of Livneh gridded daily historical data (Livneh et al., 2015; Pierce et al., 2021).

Example climatologies of LOCA2-Hybrid and LOCA2 CONUS training dataset climatologies are shown by the July Tmax and Tmin climatologies in **Figure 3a** and **3b** and by the January precipitation climatologies in **Figure 3c.** In general, there is good agreement between LOCA2-Hybrid and LOCA2 CONUS training data. For example, January Tmax LOCA2-Hybrid and LOCA2 CONUS training datasets are nearly the same, and January LOCA2-Hybrid and LOCA2 CONUS Tmax historical climatological fields are also nearly the same. But in July, there are some noteworthy differences. In July, the LOCA2-Hybrid Tmax training dataset exhibits higher temperatures in a narrow zone near the California coast and somewhat lower temperatures over the Sierra Nevada than that of LOCA2 CONUS (**Figure 3a**). Also in July, the LOCA2-Hybrid Tmin training dataset is broadly warmer than that of LOCA2 CONUS, with the exception of the California Central Valley, where LOCA2-Hybrid training is slightly cooler (**Figure 3b**).

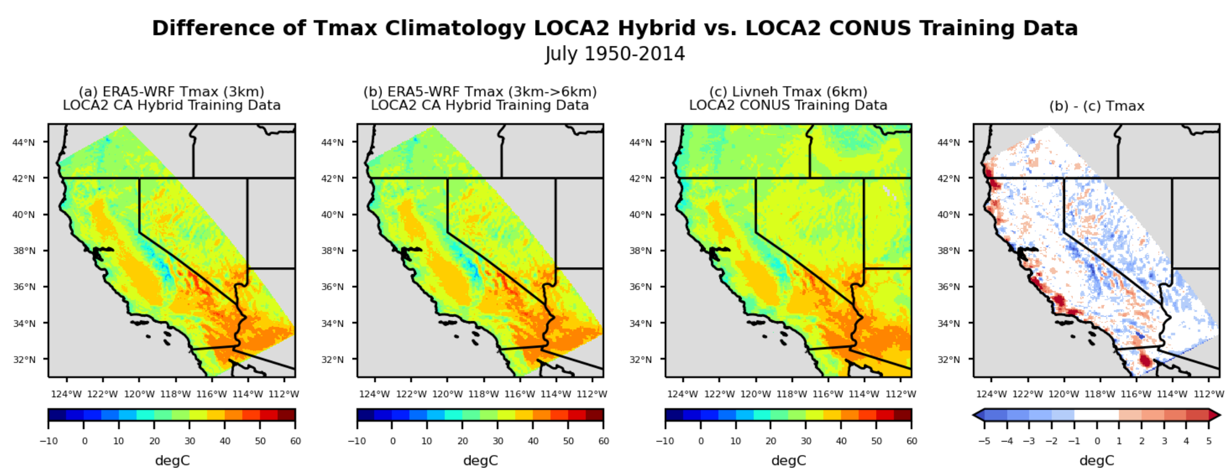

Figure 3a. Historical Tmax training datasets used in LOCA2-Hybrid and LOCA2 CONUS downscaling. The leftmost map is the July bias corrected WRF ERA5 (ERA5-WRF-BC) Tmax climatological Tmax, at 3km spatial resolution. Bias correction of WRF ERA5 Tmax is conducted using a set of daily observed surface temperatures from the Global Historical Climate Network (GHCN). The second (from left) map is a spatially-aggregated version of the leftmost 3km LOCA2-Hybrid training data, to the 6km Livneh grid. The third (from left) map is the Livneh Tmax climatology employed in the LOCA2 CONUS downscaling production. The fourth (from left) map is the difference field (ºC), consisting of the LOCA2-Hybrid minus the LOCA2 CONUS Tmax training climatologies in maps 2nd and 3rd from left.

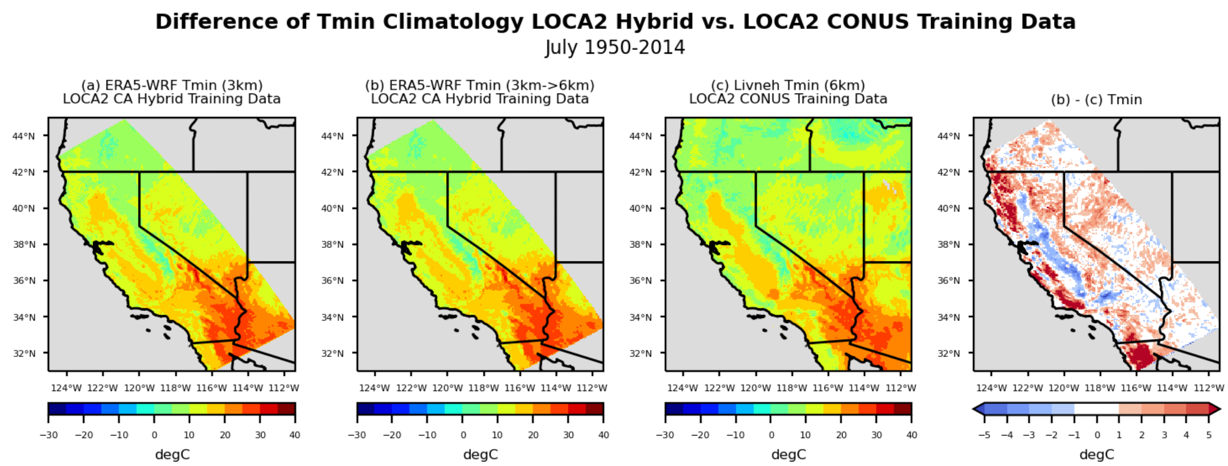

Figure 3b. Historical Tmin Training datasets used in LOCA2-Hybrid and LOCA2 CONUS downscaling. Maps, left to right, analogous to those in **Figure 1a.**

The LOCA2-Hybrid precipitation training dataset is mostly similar to that of the LOCA2 CONUS. In January the most noteworthy exception occurring just to the east of the Sierra Nevada crest, where the LOCA2-Hybrid training is lower by more than 10% of climatological averages than the LOCA2 CONUS training data (**Figure 3c**),

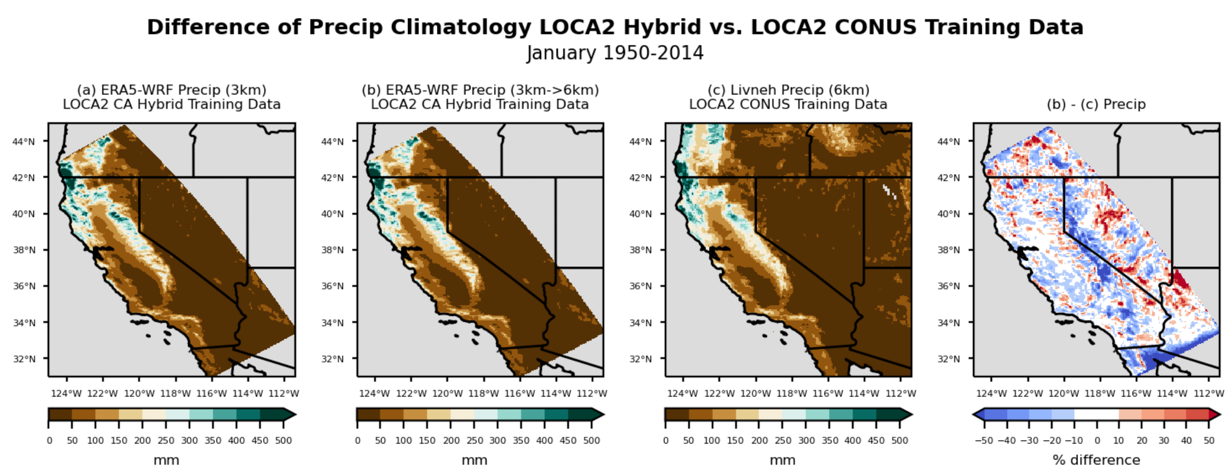

Figure 3c. Historical precipitation training datasets [mm] used in LOCA2-Hybrid and LOCA2 CONUS downscaling. Maps, left to right, analogous to those in **Figure 1a,** but difference (right-most map) is shown in % of climatological average, relative to the LOCA2 CONUS dataset (e.g., a value of 10% means that the LOCA2-Hybrid value is 10% greater than the LOCA2 CONUS value, while a value of -10% means that the LOCA2-Hybrid value is 10% less than LOCA2 CONUS).

COMPARISON: FUTURE CHANGES of LOCA2-HYBRID vs LOCA2 CONUS

In this section we present examples of monthly mean LOCA2-Hybrid vs. LOCA2 CONUS to compare results from the two approaches. In this set of comparisons, LOCA2-Hybrid 3km results have been re-gridded (aggregated) to the LOCA2 CONUS 6km grid. Selected months are presented showing the set of 5 models employed in the General Use Projections (Yao et al. 2024, Kalansky et al. 2024) and, especially the multi-model ensemble mean wherein changes are represented as the difference between the mid-21st Century 30-year 2045-2074 average and the 1950-2014 historical average. Cases presented show months where there are noteworthy differences between the two LOCA methodologies applied to the same CMIP6 projections. A comprehensive evaluation of the two methods involving individual model projections, all months and each of the three SSP scenarios is beyond the scope of this report. Here, we focus mostly upon changes in summer temperatures, with additional examples in spring temperature and winter precipitation.

As noted, differences in the respective climatological training datasets of the two sets result in similarly different 30-year temperature futures (very similar patterns and mostly similar magnitudes). Several of the differences between the two sets of projections owe largely to differences in their respective historical training datasets.

Other distinctions between the LOCA2-Hybrid and the LOCA2 CONUS projections can be seen from the differences in the changes of the two products. For Tmin, 2045-2074 minus 1950-2014 historical changes (not shown) are especially similar between the two LOCA downscalings, with magnitude of differences being mostly less than 0.5 ºC. However, Tmax changes exhibit some more substantial differences, especially near the California coast wherein LOCA2-Hybrid exhibits greater Tmax warming by about 1ºC than LOCA2 CONUS. These differences are described in the paragraphs below.

January Tmax changes in LOCA2-Hybrid and LOCA2 CONUS *(not shown*) are very nearly the same over the entire California region. July Tmax changes in LOCA2-Hybrid and LOCA2 CONUS (**Figure 4a**) are very nearly the same over most of the California region. The exception is a narrow coastal zone where LOCA2-Hybrid Tmax changes are more positive or less negative than those of LOCA2 CONUS, with differences in this region exceeding 0.5ºC.

January Tmin changes in LOCA2-Hybrid and LOCA2 CONUS (*not shown*) are very nearly the same over most of the California region. The exception is the very eastern portion of California along with most of Nevada, where LOCA2-Hybrid Tmin changes are less than LOCA2 CONUS Tmin changes, of order 0.5ºC. July Tmin changes in LOCA2-Hybrid and LOCA2 CONUS

(**Figure 4b**) are also very nearly the same over most of the California region. The exception is the pockets of locations within the narrow coastal zone where LOCA2-Hybrid Tmax changes are more positive or less negative than those of LOCA2 CONUS, with differences in this region exceeding 0.5ºC.'

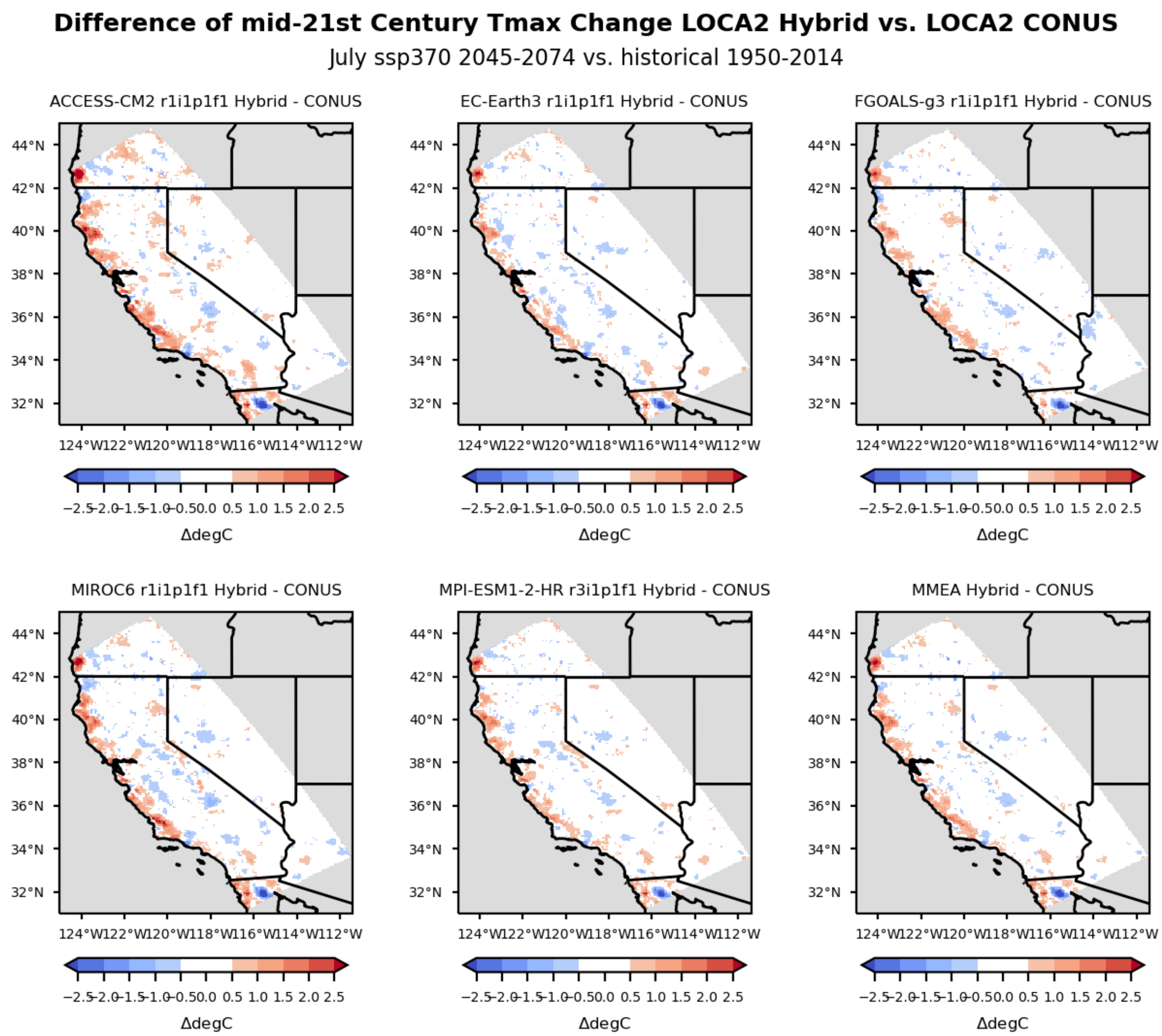

Figure 4a. Differences [ºC], LOCA2-Hybrid minus LOCA2 CONUS in projected July Tmax changes (2045-2074) minus (1950-2014)) for each of 5 General Use CMIP6 projections (upper row and left and middle of lower row) and for multi-model ensemble of the General Use projections (lower right). Notably, the LOCA2-Hybrid vs. LOCA2 CONUS differences are nearly the same as those formed from their respective historical climatological training data set (see **Figure 3**).

Springtime LOCA2-Hybrid and LOCA2 CONUS Tmax and Tmin changes exhibit some interesting differences. Notably, May maps (**Figure 5**) shown here for late 21st Century (2075-2100) vs. historical (1950-2014) for each of 3 SSPs, share similar positive differences along coastal regions with July, but also exhibit positive differences along the west slope (presumably lower elevations of Sierra Nevada). LOCA2-Hybrid vs. LOCA2 CONUS differences are positive (LOCA2-Hybrid is warmer) in the lower elevations of the western Sierra Nevada, and negative (LOCA2-Hybrid is cooler) along higher Sierra elevations. This same pattern is found for SSP245 (left), SSP370 (middle) and SSP585 (right). Understanding the pattern would benefit from analysis of how this pattern of differences aligns with changes in surface hydrology, e.g. snow cover and soil moisture, and how these might differ between the two LOCA schemes.

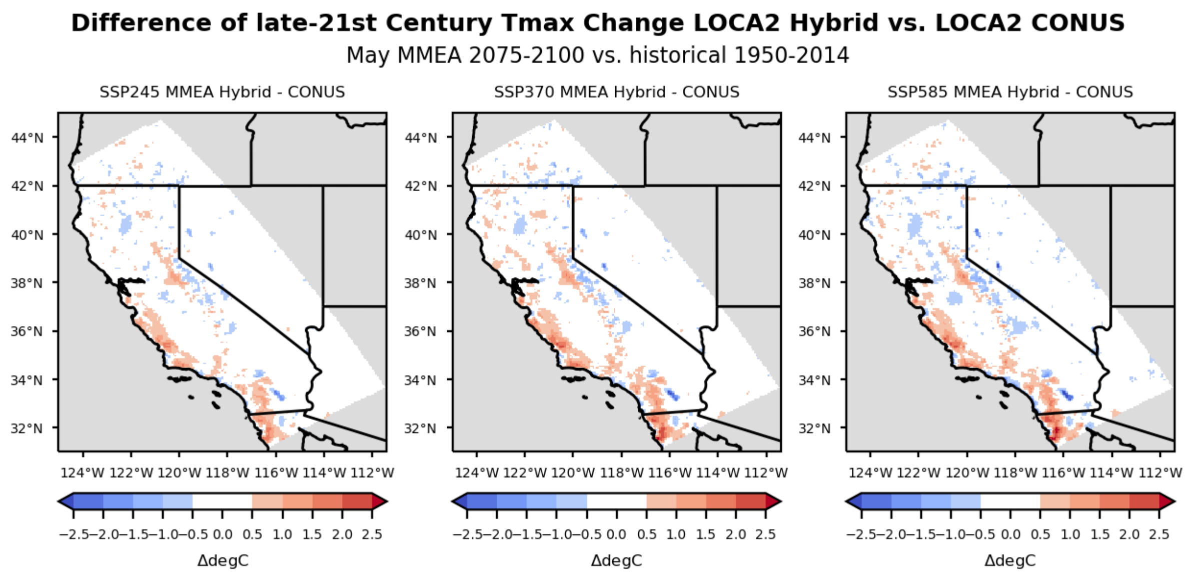

Figure 5. Differences [ºC], LOCA2-Hybrid minus LOCA2 CONUS in projected May Tmax changes ((2075-2100) minus (1950-2014)) for each of 3 SSP scenarios for 5-member ensemble of General Use CMIP6 projections.

A pointwise comparison, across two coast-to-inland transects, Sacramento and Morro Bay delineated in Figure 6a, was conducted to provide a more detailed portrait of the differences mapped in Figure 4, using Tmax as the subject example. First, the mean along-transect Tmax is shown in Figure 6b and 6c, for historical averages from the WRF-ERA5-BC used in LOCA hybrid, the Livneh dataset used in LOCA2 CONUS, and for comparison, the July Tmax from the PRISM dataset. The three climatological profiles are quite similar, with most exception being near the coast, especially along the Morro Bay transect, where Livneh (the LOCA2 CONUS climatology) July Tmax is cooler than WRF-ERA5-BC and PRISM by more than 5 ºC. Figure 6d and 6e shows July Tmax mid-21st Century vs historical changes in LOCA2-Hybrid and LOCA2 CONUS (Figures 5b and 5c) reveals detail that is not so readily seen in the mapped differences in Figure 4. In both Sacramento and Morro Bay transects, the 2045-2074 vs 1950-2014 changes in LOCA hybrid Tmax (Figures 6d and 6e) projections generally exhibit higher warming than do the LOCA2 CONUS projections, wherein the highest accentuated LOCA hybrid warming contrast is a near coastal zone having differences in excess of 1ºC. The most prominent exception in both transects and for both Tmax is a very narrow coastal zone where the LOCA hybrid changes are smaller a (though still positive) than the CONUS LOCA changes. But curiously, for the LOCA2-Hybrid July Tmax, the adjacent near-coastal zone in both Sacramento and Morro Bay transects exhibit upward spikes of warming that considerably exceed the LOCA2 CONUS warming profile there, which contrastingly shows dips in the same locations. Along both transects, the LOCA hybrid changes exhibit finer scale variation than that of CONUS LOCA changes. Some of the differences between the two must result from the fact that LOCA hybrid is calculated at higher (3km) spatial resolution than the LOCA2 CONUS 6km downscaling. As shown, relatively large differences tend to occur in regions having highest spatial gradients. But it is left to follow-up analyses to develop causal explanations of the differences.

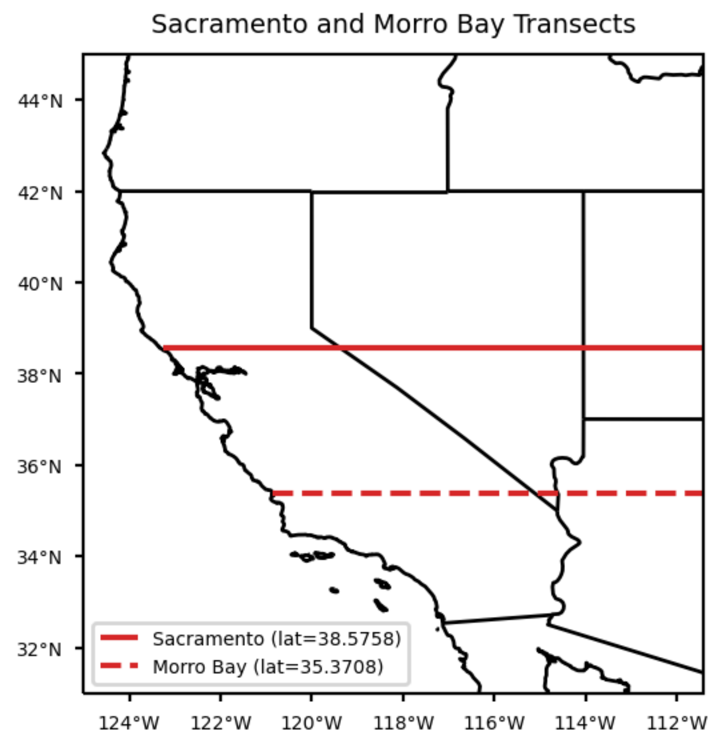

Figure 6a Zonal transects from the California coast to the inland boundary crossing through Sacramento (north-most transect) and crossing through Morro Bay (south-most transect).

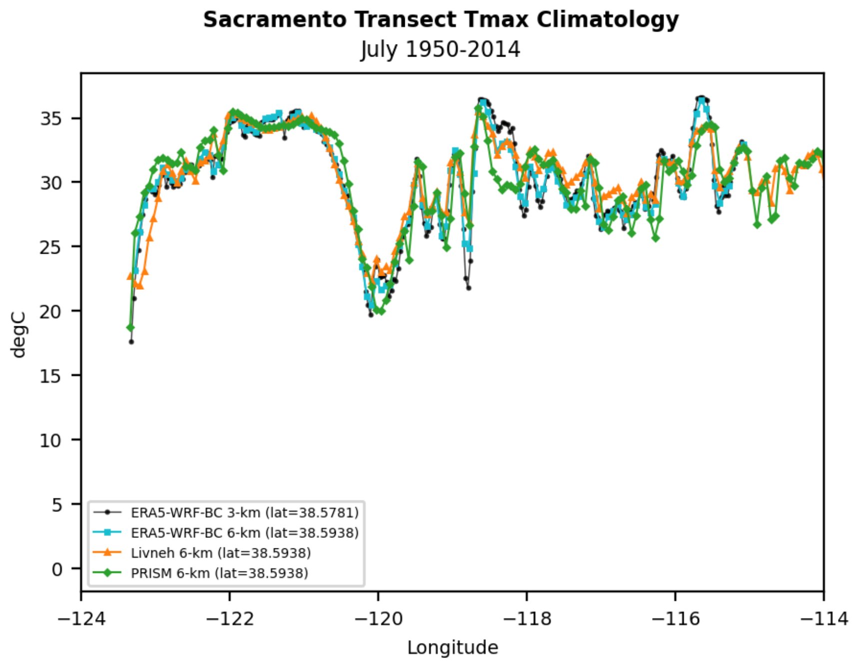

Figure 6b Mean (1950-2014) Tmax, July, for ERA5-WRF-BC (LOCA2-Hybrid climatology, at its native 3km spatial resolution (black) and upscaled to 6km blue), Livneh (LOCA2 CONUS climatology, orange) and PRISM along the Sacramento longitudinal transect.

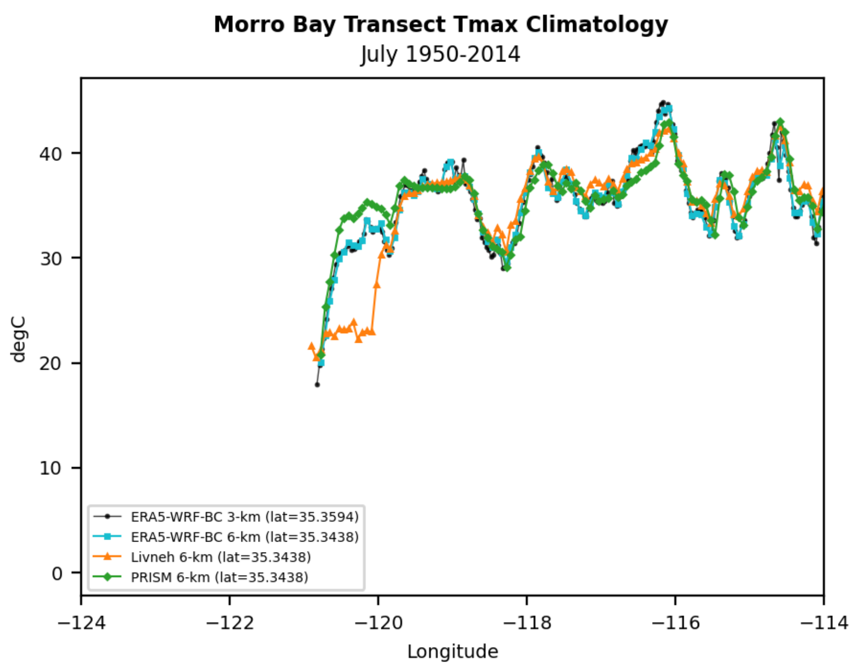

Figure 6c Mean (1950-2014) Tmax, July, for ERA5-WRF-BC (LOCA2-Hybrid climatology, at its native 3km spatial resolution (black) and upscaled to 6k (blue), Livneh (LOCA2 CONUS climatology, orange) and PRISM along the Morro Bay longitudinal transect.

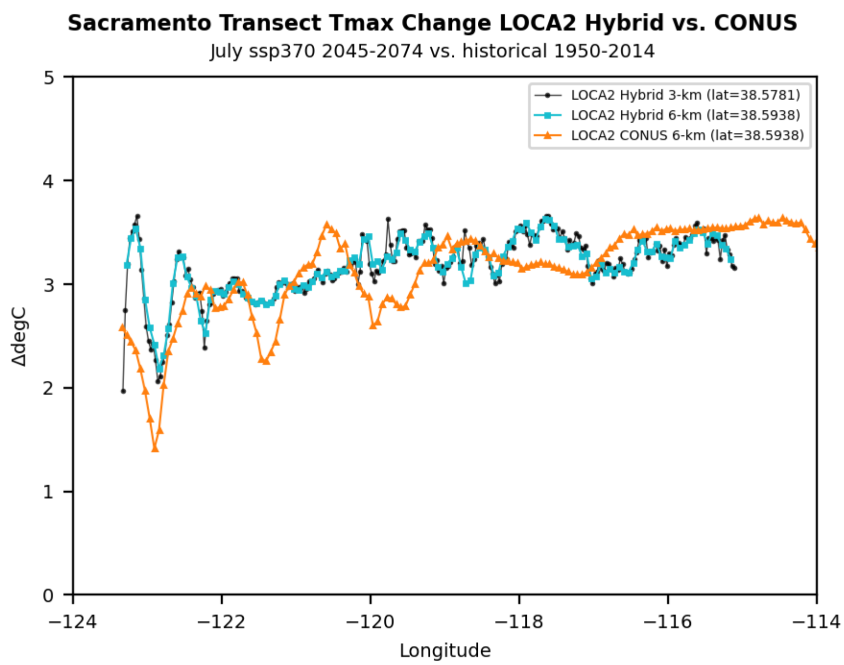

Figure 6d. Mean Tmax, July changes (2045-2074 minus 1950-2014) of LOCA2-Hybrid , at its native 3 km spatial resolution (black) and upscaled to 6 km (blue), and LOCA2 CONUS, orange, along the Sacramento longitudinal transect.

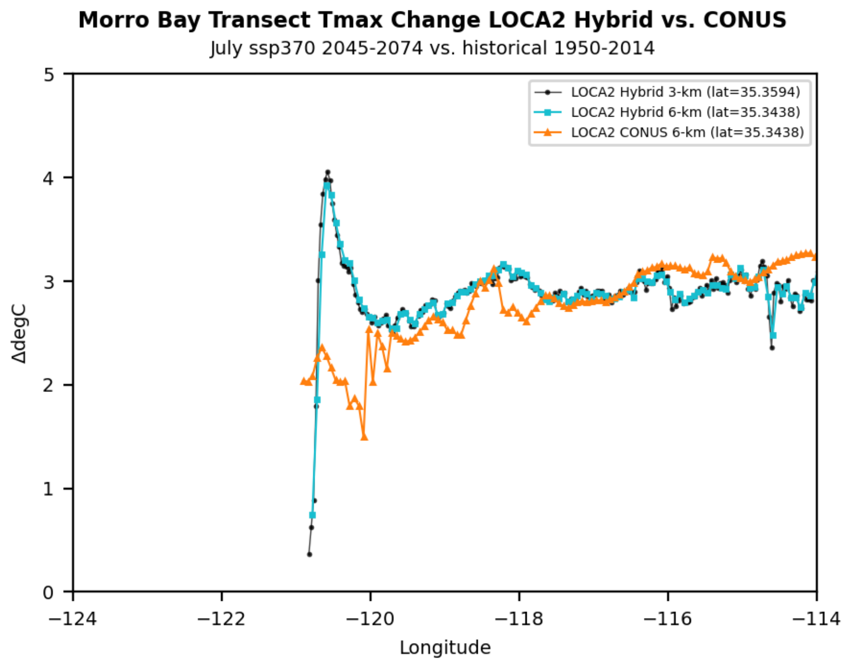

Figure 6e. Mean Tmax, July changes (2045-2074 minus 1950-2014) of LOCA2-Hybrid , in its native 3km spatial resolution (black) and upscaled to 6km (blue), and LOCA2 CONUS, orange, along the Morro Bay longitudinal transect.

January precipitation changes in both LOCA2-Hybrid and LOCA2 CONUS (**Figure 7a**) over much of California are positive and cover most of the California and Nevada region. The LOCA2-Hybrid and LOCA2 CONUS mid-21st Century changes differ very little. The most notable exception occurs in the lee of the Sierra Nevada, where LOCA2-Hybrid is marked by negative (less increase or greater decrease) than LOCA2 CONUS, with differences in their respective changes exceeding 20% of their climatological values. February precipitation mid-21st Century changes (**Figure 7b**) are also positive but not as strongly as in January, and the differences between LOCA2-Hybrid and LOCA2 CONUS are minimal.

July precipitation changes (not shown) are dominated by larger (more positive or less negative) changes in LOCA2-Hybrid than LOCA2 CONUS. These differences are widespread over southern and eastern California and Nevada, where differences in their respective changes exceed 30% of their climatological values. However, the very dry summer conditions in California make these summer differences of less interest compared to the wet season.

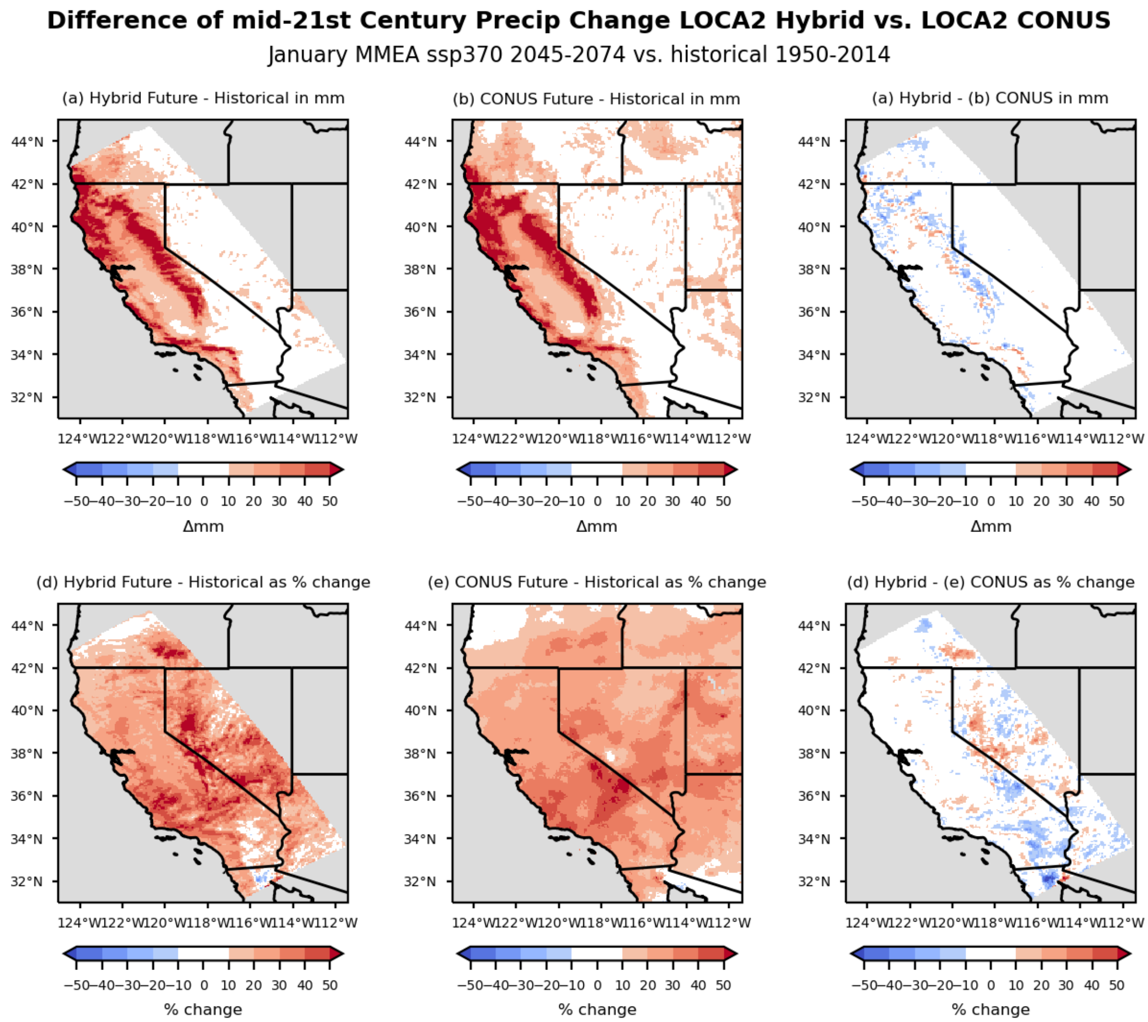

Figure 7a. Left and Middle: Projections of mid-21st century (2045-2074) 30 year average change relative to historical (1950-2014) period January precipitation for LOCA2-Hybrid and LOCA2 CONUS projections. Right-most maps are differences of LOCA2-Hybrid minus LOCA2 CONUS changes. All maps for multi-model (5 General Use) mean. Results of upper and lower rows in mm and in % of historical climatological mean, respectively.

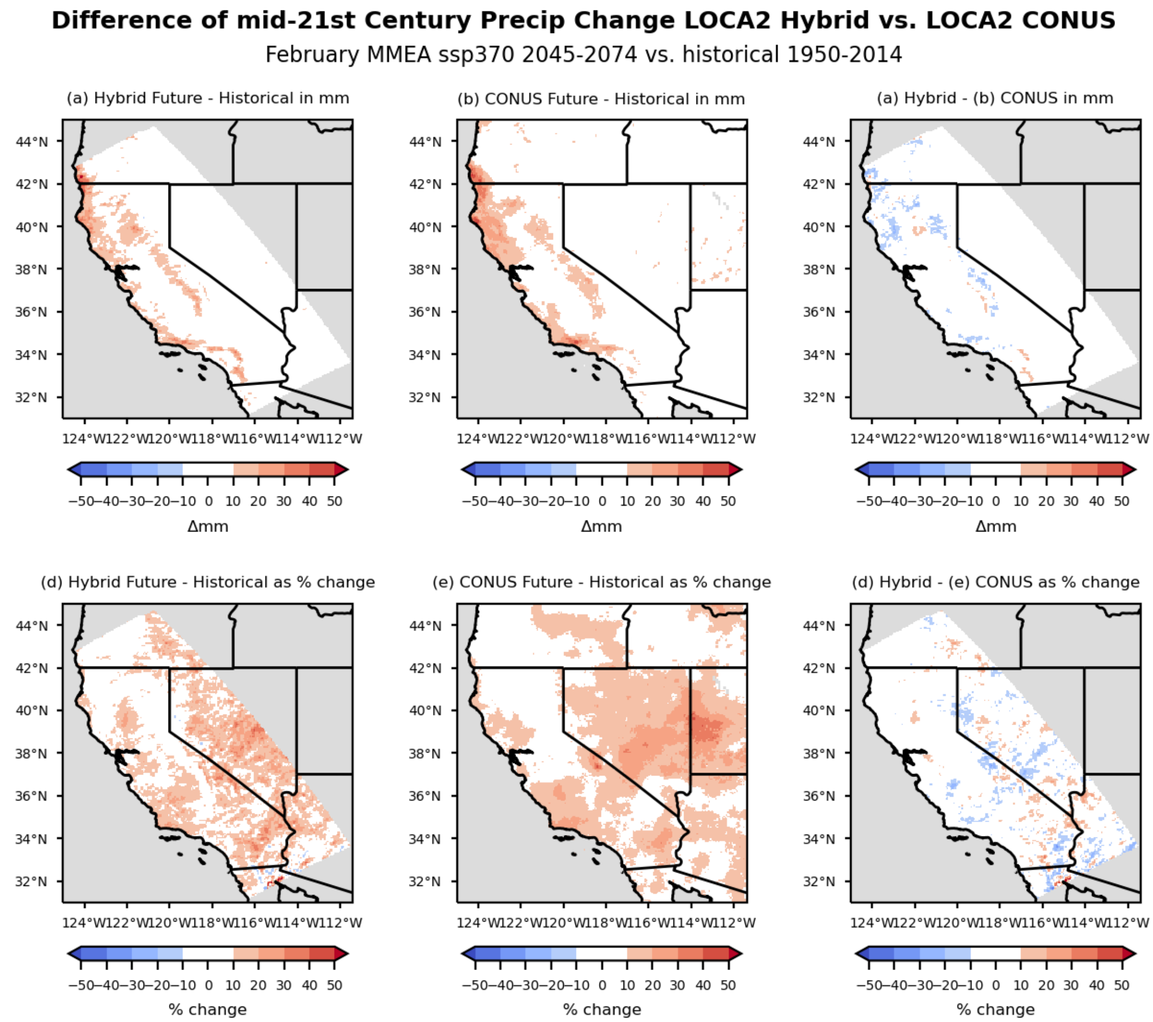

Figure 7b. As in Figure 7a but for February.

CONCLUDING THOUGHTS:

These comparisons between LOCA2-Hybrid and LOCA2 CONUS downscaled Tmax projections of mid-21st Century change reveals considerable agreement in a large portion of California but substantial differences in certain regions. Comparisons between LOCA2-Hybrid and LOCA2 CONUS downscaled precipitation during January exhibit broadly more positive-leaning changes produced by LOCA2-Hybrid projections than do the LOCA2 CONUS projections from the same set of models. These are a very limited set of cases, but they are chosen for their representation of changes during California's primary summer heat and core winter water delivery seasons, so they compel some suggestions for further investigation. Does some part of these differences arise from differences in the respective climatological underpinning used in LOCA2-Hybrid vs. LOCA2 CONUS? Is there effects of higher spatial resolution used in LOCA2-Hybrid than that of LOCA2 CONUS? And, to what extent do methodological differences, perhaps representing physical processes that might be contained (or not) in the respective downscaling schemes? Further investigation should extend across all months consider shorter time scales than the multi-decade mean differences employed here to develop better physical or process understanding.

References

Brown, T., G. Mills, S. Harris, D. Podnar, H. Reinbold, and M. Fearon, 2016: A bias corrected WRF mesoscale fire weather dataset for Victoria, Australia 1972-2012. *Journal of Southern Hemisphere Earth Systems Science*, *66*(3), 281-313.

Clemesha, R. E. S., A. Gershunov, S. F. Iacobellis, A. P. Williams, and D. R. Cayan, 2016: The Northward March of Summer Low Cloudiness along the California Coast. Geophys. Res. Lett., 43, DOI:10.1002/2015GL067081

Hersbach, H, Bell, B, Berrisford, P, et al. The ERA5 global reanalysis. Q J R Meteorol Soc. 2020; 146: 1999–2049. https://doi.org/10.1002/qj.3803

Kalansky, J., Yao, P., Cayan, D. R., and D. W. Pierce, 2024: Data Adoption Justification Memo (for California's Fifth Climate Change Assessment): General Use Projections. Available online at https://www.energy.ca.gov/media/10706

Krantz, W., D. W. Pierce, N. Goldenson, and D. R. Cayan, 2021: Memorandum on Evaluating Global Climate Models for Studying Regional Climate Change in California. Interim deliverable for EPC-20-006, 24 pp. Available online at https://www.energy.ca.gov/media/7264

Livneh, B., T. J. Bohn, D. W. Pierce, F. Munoz-Arriola, B. Nijssen, R. Vose, D. R. Cayan, and L. Brekke, 2015: A spatially comprehensive, hydrometeorological data set for Mexico, the U.S., and Southern Canada 1950-2013. Scientific Data, v. 2, article 150042 (2015). doi:10.1038/sdata.2015.

Panofsky, H.A. and Brier, G.W. (1968) Some Applications of Statistics to Meteorology. Earth and Mineral Sciences Continuing Education, College of Earth and Mineral Sciences.

Pierce, D. W., D. R. Cayan, and B. L. Thrasher, 2014: Statistical downscaling using localized constructed analogs (LOCA). J. Hydrometeorology, v. 15, p. 2558, doi:10.1175/JFM-D-140082.1

Pierce, D. W., D. R. Cayan, E. P. Maurer, J. T. Abatzoglou, and K. C. Hegewisch, 2015a: Improved bias correction techniques for hydrological simulations of climate change. J. Hydrometeorology, v. 16, p. 2421-2442. DOI: http://dx.doi.org/10.1175/JHM-D-14-0236.1

Pierce, D. W. and D. R. Cayan, 2015b: Downscaling humidity with Localized Constructed Analogs (LOCA) over the conterminous United States. Climate Dynamics, DOI 10.1007/s00382015-2845-1.

Pierce, D. W., J. F. Kalansky, and D. R. Cayan, 2018: Climate, drought, and sea level rise scenarios for California's Fourth Climate Change Assessment. California's Fourth Climate

Change Assessment, California Energy Commission and California Natural Resources Agency, report CCCA4-CEC-2018-006. https://www.energy.ca.gov/sites/default/files/201911/Projections_CCCA4-CEC-2018-006_ADA.pdf

Pierce, D. W., L. Su, D. R. Cayan, M. D. Risser, B. Livneh, and D. P. Lettenmaier, 2021: An Extreme-Preserving Long-Term Gridded Daily Precipitation Dataset for the Conterminous United States. Journal of Hydrometeorology, v. 22, p. 1883-1895. https://doi.org/10.1175/JHMD-20-0212.1

Pierce, D. W., S. Rahimi, D. R. Cayan, and J. Kalansky, 2023a: Bias Correction in the WRF and LOCA2 Projections**.** Data Justification Memo for EPC-20-006 Development of Climate Projections for California and Identification of General Use Projections, January, 2024, available at https://www.energy.ca.gov/media/9326

Pierce, D. W., S. Rahimi, S. Iacobellis, D. R. Cayan, and J. Kalansky, 2023b: LOCA2 Training Data. Data Justification Memo for EPC-20-006 Development of Climate Projections for California and Identification of General Use Projections, January, 2024, available at https://www.energy.ca.gov/media/9328

Pierce, D.W., Cayan, D.R., Rahimi, S. and J. Kalansky, 2023c. LOCA version 2 Hybrid Downscaling. California Energy Commission Data Adoption Justification Memo (for California's Fifth Climate Change Assessment). ttps://www.energy.ca.gov/sites/default/files/2024-03/04_HybridDownscaling_DataJustificationMemo_Pierce_Adopted_ada.pdf

Rahimi-Esfarjani, S.: Memorandum on the Development and Availability of Dynamically Downscaled Projections Using WRF Interim deliverable to the California Energy Commission. Available at: https://www.energy.ca.gov/sites/default/files/2022-09/20220907_CDAWG_MemoDynamicalDownscaling_EPC-20-006_May2022-ADA.pdf

Rahimi, Oct 2022. Memo on the Evaluation of Downscaled GCMs Using WRF. Available at https://www.energy.ca.gov/sites/default/files/2025-07/d_PerformanceEval_of_Dyn_Downscaled_GCMs_Using_WRF_oct2022_ada.pdf

Skamarock, W. C., J. B. Klemp, J. Dudhia, D. O. Gill, Z. Liu, J. Berner, W. Wang, J. G. Powers, M. G. Duda, D. M. Barker, and X.-Y. Huang, 2019: A Description of the Advanced Research WRF Version 4. *NCAR Tech. Note NCAR/TN-556+STR*, 145 pp.

Thrasher, B., Maurer, E. P., McKellar, C., and Duffy, P. B.: Technical Note: Bias correcting climate model simulated daily temperature extremes with quantile mapping, Hydrol. Earth Syst. Sci., 16, 3309–3314, https://doi.org/10.5194/hess-16-3309-2012, 2012.

Wessel, P., Smith, W.H.F., Scharroo, R., Luis, J.F. and Wobbe, F. (2013) Generic Mapping Tools: Improved Version Released. Eos, Transactions, American Geophysical Union, 94, 409-410. https://doi.org/10.1002/2013EO450001

Yao, P., D. W. Pierce, D. Cayan, and J. Kalansky, 2024: Hourly station data memo for the Fifth California Climate Assessment, Data Justification Memo EPC-20-006 Development of Climate Projections for California and Identification of General Use Projections, January 2024, https://www.energy.ca.gov/sites/default/files/2024-10/07_General_Use_Projections_Data_Justification_Sept2024_ada.pdf