Data Adoption Justification Memo (for California's Fifth Climate Change Assessment)

Bias Correction in the WRF and LOCA version 2 Projections

David W. Pierce, Stefan Rahimi, Daniel R. Cayan, Julie Kalansky, Scripps Institution of Oceanography, UCSD & UCLA

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<u>Methods and Prior Relevant Work</u>

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. Specific details on the bias correction methods used with dynamical downscaling via the Weather Research and Forecasting (WRF) model and in the statistical downscaling Localized Constructed Analogs version 2 (LOCA2 hereafter) technique are described in the data justification memos for those individual products.[1] The purpose of this memo is to give a high-level overview of bias correction so climate data users can better understand the context of how bias correction is used differently in the different products.

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).

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 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

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[1] The next generation of climate projections for California, developed with support from the state's EPIC program (CEC award EPC-20-006) and also available for California's Fifth Climate Change Assessment, has produced dynamically downscaled projections (using WRF) and hybrid (statistically and dynamically) downscaled projections (using WRF and LOCA2).

by season and how extreme the value is. Four of eight WRF runs apply a monthly mean bias correction to the GCM values before the downscaling step (Colette et al. 2012, Bruyere et al., 2014). In the WRF data this is termed *a priori* bias correction because the step occurs before the WRF model ingests the GCM data. The GCM climatological mean wind and temperature fields are forced to match the ERA5 reanalysis (Hersbach et al. 2020) when *a priori* bias correction is applied to WRF.

All the LOCA2 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". Four of eight of the WRF runs have a similar bias correction applied after the WRF downscaling step, which is termed "*a posteriori* bias correction" since it happens after the WRF run. Different kinds of WRF downscaled GCM model run results are available, some with *a priori* bias correction, some with both *a priori* and *a posteriori* bias correction, and some with no bias correction.

The bias correction of projected future climate also differs between LOCA2 and WRF. In WRF, the monthly mean bias correction values computed over the historical period are retained unchanged in the future projections. LOCA2's PresRat approach uses a more complex scheme where the GCM-projected changes in variables by quantile are preserved in the downscaled projections.

QA/QC and Uncertainty

Bias correction is typically performed using all available observations or approximations of reality from reanalyses, which means that comparing the bias corrected results to observations is not an independent evaluation. Pierce et al. 2024 describes how QA/QC is accomplished in the generation of the LOCA2 training data, which is used for the LOCA2 bias correction. In brief, sets of training data are made leaving various stations out of the data set construction, then the results compared to when all stations are used. This approach is called "cross validation".

Another approach is to compare the bias corrected output to observations on measures that were not directly used in the bias correction. For example, the WRF runs with only *a priori* bias correction use the monthly means of temperature and winds. Comparisons of the modeled extremes against observational products can provide a fair evaluation of bias given the different phasing of internal variability between GCMs (think of them as alternate realities) and historical observations. For the dynamically downscaled GCMs without *a priori* bias correction described in the *Memo on the Evaluation of Downscaled GCMs Using WRF* (Rahimi-Esfarjani 2022b), comparisons of downscaled temperature and precipitation against historical observations are an even more just evaluation of bias.

One fundamental uncertainty that needs to be kept in mind is that observations are incomplete and prone to instrumentation, recording, or transmission errors, and typically under sample high elevations. Bias correcting to observations with undetected or uncorrected errors will give a result that mirrors those observational errors. Examples of these kinds of errors are given in Pierce and Cayan (2019). Although efforts were made to remove observational errors in this work, they can still slip by the QC process. Additionally, some variables such as wind, humidity, and radiation are sparsely observed and have not been monitored over long enough periods (a few decades or more) to adequately capture the full range of variability. These observational data shortcomings can be especially acute in describing high impact extremes (e.g., heavy precipitation or high wind events).

Lastly, all bias correction methods assume that model biases observed over the historical period continue unchanged into the future. Although this is a reasonable assumption, it should be kept in mind that this assumption is made. Model groups spend considerable effort on the problem of reducing model biases, and, historically, such biases have generally decreased over time as models improve.

Guidance or Caveats on Best Practices for Use of Data Products

Nearly all GCMs and dynamic regional models (such as WRF) yield results that contain biases comparable to climate changes projected in the next few decades. These biases may be too large to support direct use of non-bias corrected model results as input to models assessing climate change vulnerability and/or impacts. Thus, bias corrected climate projections are the best option for many users.

However, not all users want bias corrected WRF data. Researchers performing a process study or examining the balance of terms in the WRF need outputs that are physically linked. This linkage is only retained in experiments that contain no post-downscaling bias correction since the process alters the relationships between the high-resolution outputs (e.g., temperature and precipitation) and other physical variables of interest to process modelers a. On the other hand, WRF outputs by themselves, even with *a priori* bias correction, may still be too biased for use in demand forecasting and hydrology models hence motivating the use of the post-downscaling bias correction products.

Some stakeholders use simple “projected change” or delta methods, where the projected model change is used to drive the application model or analysis. In this case whether or not bias correction is used is of less importance, although even then we find that *a priori* bias correction can affect WRF’s predicted changes. Since *a priori* bias correction has been shown to increase the physical realism of the WRF simulations in the historical period, it is believed that the changes in future trends arising from *a priori* bias correction likely represent an improvement as well, but this is an area of active research.

We refer the reader to the specific LOCA2 (Pierce et al. 2024) and WRF (Rahimi-Esfarjani 2022a) data justification memos for details of the bias correction methods of those products. Here we emphasize that it is important for climate data users to understand what kind of biases their applications are sensitive to when selecting which products to use. Best practice is to evaluate the different data products for those key biases. To save different groups repeating the same work, evaluations of a variety of common LOCA2 bias are available at https://loca.ucsd.edu/~pierce/analysis_CAhyb/

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