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Bias correction can modify climate model-simulated precipitation changes without adverse affect on the ensemble mean

E. P. Maurer[1] **and D. W. Pierce**[2]

[1]Civil Engineering Dept., Santa Clara University, Santa Clara, CA, USA
[2]Division of Climate, Atmospheric Science, and Physical Oceanography, Scripps Institution of Oceanography, La Jolla, CA, USA

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Correspondence to: E. P. Maurer (emaurer@engr.scu.edu)

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Abstract

When applied to remove climate model biases in precipitation, quantile mapping can in some settings modify the simulated trends. This has important implications when the precipitation will be used to drive an impacts model that is sensitive to changes in precipitation. We use daily precipitation output from 12 general circulation models (GCMs) over the conterminous United States interpolated to a common 1° grid, and gridded observations aggregated to the same scale, to compare precipitation differences before and after quantile mapping bias correction. The change in seasonal mean (winter, DJF, and summer, JJA) precipitation between different 30-yr historical periods is compared to examine (1) the consensus among GCMs as to whether the bias correction tends to amplify or diminish their simulated precipitation trends, and (2) whether the modification of the change in precipitation tends to improve or degrade the correspondence to observed changes in precipitation for the same periods. In some cases, for a particular GCM, the trend modification can be as large as the original simulated change, though the areas where this occurs varies among GCMs so the ensemble median shows smaller trend modification. In specific locations and seasons the trend modification by quantile mapping improves correspondence with observed trends, and in others it degrades it. In the majority of the domain the ensemble median is for little effect on the correspondence of simulated precipitation trends with observed. This highlights the need to use an ensemble of GCMs rather than relying on a small number of models to estimate impacts.

1 Introduction

In translating simulated precipitation projections produced by general circulation models (GCMs) for local and regional climate impacts studies, a process of downscaling is needed (Christensen et al., 2007; Fowler et al., 2007; Murphy, 1999). In any downscaling process there is by necessity some form of bias correction to remove the timeinvariant GCM biases, allowing the signal, or change, simulated by the GCM to be isolated to some degree from the systematic errors.

A common method for bias correction is quantile mapping (QM), which has been shown to be an effective method for removing GCM some biases at relatively little computational expense (Li et al., 2010; Maraun et al., 2010; Panofsky and Brier, 1968; Piani et al., 2010; Themeßl et al., 2011; Wood et al., 2004). This method has been employed in creating several widely used data sets of downscaled GCM output for the United States and global land areas (Girvetz et al., 2009; Maurer et al., 2007). The use of these datasets in hundreds of studies, and the extensive application of QM by many others, has led to recent efforts to study some of the assumptions and effects of QM bias correction (Maraun, 2012, 2013; Maurer et al., 2013).

One important effect of QM is that it can change the GCM trend, so that the raw GCM simulated change is modified during the bias correction process, an effect that can be large relative to other sources of uncertainty such as variability among GCMs (Brekke et al., 2013; Hagemann et al., 2011; Maraun, 2013; Pierce et al., 2013; Themeßl et al., 2011). This has raised concerns regarding the effect of changing the sensitivity of precipitation as simulated by GCMs, especially for water-constrained regions where climate adaptation plans hinge on projected changes in water supply (Barsugli, 2010). In this paper we examine the effect of QM on projected precipitation changes, and focus on the question of whether the effect degrades the skill of the GCM projections.

2 Methods and data

As an observational baseline, we used the daily precipitation dataset of Livneh et al. (2013), which has a spatial extent of the conterminous United States, a spatial resolution of 1/16° (approximately 6 km), and includes the period 1915–2011. This was aggregated to a 1° spatial resolution for this bias correction exercise, which is a typical spatial resolution used when bias correcting GCMs (e.g., Li et al., 2010; Wood et al., 2004). The 1° spatial scale was selected here to correspond to a scale finer than the highest resolution GCM used in this study. We included only those 1° cells where at least 25 % of the area was land area included in the Livneh et al. (2013) data set.

We obtained simulated daily precipitation from the historical runs for 12 climate models (while some are more properly termed earth system models, for simplicity here we use GCM to refer to them), listed in Table 1, from the CMIP5 multi-model ensemble archive (Taylor et al., 2012). For all of the GCMs we used the run identified as r1i1p1, with the exception of GISS-E2-R for which we used r6i1p1 since that had the available variables and periods for this study. From the CMIP5 historical runs we extracted the 1915–2005 period to have overlapping years for both the observed and GCM-simulated data. The GCM data were also bilinearly interpolated onto the same 1° grid as the observations.

QM is extensively discussed elsewhere (e.g., Gudmundsson et al., 2012; references cited above) and only a brief summary is presented here. QM bias correction is an empirical statistical technique that matches the quantile for a GCM simulated value to the observed value at the same quantile. The quantiles are determined by sorting GCM output and observations for the same historical base (or calibration) period, and constructing cumulative distribution functions (CDFs) for each. We used a version of QM bias correction essentially following Maurer et al. (2010), with one variation. Maurer et al. (2010) considered each month independently, so that for January a 30-yr base period would have a CDF defined by 31 days × 30 yr = 930 points. One modification for this application is that, to avoid abrupt inconsistencies between months, we used a moving 31-day window centered on each day, producing a separate set of CDFs for each day of year (Dobler et al., 2012; Thrasher et al., 2012). This method employs a non-parametric quantile mapping, that is, there is no fitting of a theoretical probability distribution to the data in creating the CDFs. While both parametric and non-parametric approaches are widely used in QM, non-parametric methods have shown higher skill in reducing systematic errors in modeled precipitation, both for means and extremes (Gudmundsson et al., 2012).

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We focused initially on two 30-yr periods: 1976–2005 and 1916–1945, and extended the study to also compare 1946–1975 and 1916–1945. Most CMIP5 GCM simulations have been shown to reproduce important climate features, such as ENSO and its teleconnections to United States precipitation (Polade et al., 2013), with 30-yr periods proving adequate for such studies (Sheffield et al., 2013; Zhang et al., 2012). We compared the raw interpolated GCM ("Raw") and the bias corrected ("BC") shifts relative to observations ("obs") in precipitation between the two periods for winter (DJF) and summer (JJA). We used a difference in daily precipitation, in mm, as a metric, for example:

$$\Delta P_x = \overline{P}_{x(1976-2005)} - \overline{P}_{x(1916-1945)}, \text{mm d}^{-1} \quad (1)$$

where the subscript x is either "obs", "raw" or "bc" for observations, raw GCM, or bias corrected GCM precipitation, and the overbar indicates a 30-yr mean. To quantify the effect of the BC on the precipitation change between the two periods, we used an index defined as:

$$\text{Index} = |\Delta P_{\text{bc}} - \Delta P_{\text{obs}}| - |\Delta P_{\text{raw}} - \Delta P_{\text{obs}}|, \text{mm d}^{-1} \quad (2)$$

where vertical bars are the absolute value. This index has the property of having values greater than 0 where the bias correction degrades the correspondence between the climate model and observed precipitation sensitivity.

3 Results and discussion

Figure 1 presents an illustration of one way in which quantile mapping can change the trend or shift simulated by a GCM. The plot uses a synthetic data set of daily precipitation generated using a gamma distribution, similar to Piani et al. (2010). The data for synthetic observations have a mean of 30, as do the data for synthetic GCM for the overlapping historic period, so the GCM shows no bias in mean daily precipitation for

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the overlapping historic period, but is given a −30 % bias (underestimate) in standard deviation. The future GCM projection assumes a 40 % increase in mean relative to the historic GCM. The arrows indicate what would happen during quantile mapping of the GCM raw future projection for two values corresponding to a low (20th percentile) and high (80th percentile) value. For the 80th percentile value, the future GCM value of 55.7 corresponds to a 95th percentile for the raw historic GCM data. The 95th percentile of the observations is 63.7, which becomes the new bias-corrected future GCM value. Similarly, the 20th percentile raw future GCM value of 25.9 is mapped to a bias corrected value of 23.8. The brackets above and below the plot show that the quantile mapping increases the simulated change at both values, with the original changes being the difference between the raw future and historic GCM, and the post-BC change being the difference between the bias corrected values and the observations. The original change at the 80th percentile is 15.6, and the post-BC change is 21.2; at the 20th percentile the original change is 7.4 and the post-BC change is 8.6.

Figure 2 continues with the synthetic data from Fig. 1, but presents probability distribution functions to illustrate more clearly the effect of the imposed bias in variance on the projected change through the bias correction process. Figure 2a shows that the 40 % increase in the raw GCM data is amplified to a 56 % increase by the QM process. If the synthetic distribution were symmetrical, a comparable decrease in GCM simulated mean would be amplified in the opposite direction, and if projected changes were negative as often as positive, then this amplifying effect would be offset and the quantile mapping would have little net effect on trends or shifts. However, because the distributions in Fig. 2a are bounded and positively skewed, even when equivalent increases and decreases are projected, the net effect of an underestimated variance is for quantile mapping to amplify the trend. This is illustrated in Fig. 2b, where the same observed and raw GCM historic distributions are used, but a 40 % decrease in mean value is imposed on the raw future GCM projection. In this case, the shift is only slightly affected by quantile mapping, changing from a 40 % decrease to a 39 % decrease. Thus, an underestimate of variance for a bounded, positively skewed distribution, common for

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daily precipitation (Wilks, 1989), will have a tendency during quantile mapping bias correction to amplify projected trends or shift. Conversely, overestimation of variance will tend to damped projected trends.

The connection between bias correction, the variance, and the trend can be understood more clearly by analyzing a simple change in the median. Let $M^E_{0.5}$ be the model median in the early period, with the subscript 0.5 indicating the percentile and the superscript being E for the early period. The model median in the late period is then $M^L_{0.5}$, and we are interested in the effect of bias correction on the model-predicted change in median, $M^L_{0.5} - M^E_{0.5}$. Will bias correction amplify or reduce this change? Assuming the change is non-zero, we can write $M^L_{0.5} - M^E_p$, where $p \neq 0.5$ is the percentile value of the new model median in the old model distribution. The raw model-projected change in median is then simply $M^E_p - M^E_{0.5}$. QM will map a model value with percentile p in the early period to the observed value at the same percentile: $\mathrm{QM}\left(M^E_p\right) = O^E_p$, where O indicates an observed value. The bias corrected change in median is therefore $\mathrm{QM}\left(M^E_p\right) - \mathrm{QM}\left(M^E_{0.5}\right) = O^E_p - O^E_{0.5}$.

Since we have already stipulated $p \neq 0.5$, we can compare the magnitude of the bias corrected to original change in median using a ratio:

$$\mathrm{Ratio} = \frac{O^E_p - O^E_{0.5}}{M^E_p - M^E_{0.5}} \tag{3}$$

This ratio is < 1 (bias correction reduces the model change) when the model difference between the pth percentile and median value is larger than the observed difference between the pth percentile and the median value – i.e., when the model has too much variance. Similarly, this ratio will be > 1, and bias correction will increase the model change, when the model has less variance than observed. Furthermore, Eq. (3) indicates that QM does not alter the sign of the model-predicted change (at least in this simple case) and that the alteration of the change is insensitive to any positive or

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negative bias between the model and observations, being affected only by the relative variance of the two.

In reality trends in non-normally distributed variables cannot be represented just by changes in the median, and GCMs exhibit much more complex biases than simply an overestimate or underestimate of variance, with differing biases at different times, in different seasons, and at different quantiles, for example (Boberg and Christensen, 2012; Maurer et al., 2013; Themeßl et al., 2011), all of which can affect the change in climate sensitivity through by QM. Thus, simply characterizing a GCM as exhibiting a certain bias in standard deviation will not exactly predict the effect of bias correction on trends. In any case, for illustration Fig. 3 shows the ensemble median of biases in standard deviation, expressed as a ratio of GCM to observed standard deviation, for the 12 GCMs included in this study for two seasons: DJF and JJA. This shows areas where there appears to be consistent underprediction of standard deviation by a majority of GCMs, such as the Southeastern portion of the domain. This means there may be a potential for the trends in the raw output from many of the GCMs to be modified by the bias correction process.

Analyzing actual precipitation projections, Figs. 4 and 5 show that bias correction does not generally change the pattern of regions that are projected to become wetter or drier, as suggested by Eq. (3), since the left and center columns are broadly similar. However, the difference between the bias corrected and raw GCM precipitation changes for some regions is of a magnitude that is comparable to the projected change itself. While the differences (right columns in Figs. 4 and 5) show that there are large areas where the BC process produces a wettening or drying effect for each GCM, there is considerable variation among the GCMs.

While not shown here, for JJA precipitation the changes due to the BC process for each GCM appear slightly less prominent than for DJF relative to the raw GCM precipitation changes between the two periods. Figure 6 shows the ensemble median change and the interquartile range (IQR) between the BC and Raw precipitation differences for the two periods for both DJF and JJA. The left column represents the ensemble median

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effect of BC on the seasonal mean precipitation difference between 1976–2005 and 1916–1945. The IQR in Fig. 6 is analogous to the standard deviation, representing the spread of the GCMs about the median. While not the focus of this effort, some spatial correspondence between the areas with biases in standard deviation in Fig. 3 and the median effect of bias correction on the trend in precipitation in Fig. 6 is evident.

While the changes in precipitation sensitivity induced by the BC process in Fig. 6 would raise concern, for many areas of the domain they are small in comparison to the observed difference in mean precipitation between the two periods, as shown in Fig. 7 (note the difference in scales between Figs. 6 and 7). However, there are two important points illustrated by Figs. 6 and 7. First, while the modification of the change in precipitation via the BC process in general has a low magnitude relative to the overall trend, at individual points this can be too broad a statement. For example, For the DJF median panel in Fig. 6, there are two red grid cells along the central West coast, with a median effect of the BC on the precipitation trend of 0.1–0.2 $mm\,d^{-1}$. This could be an important difference based on the observed differences in Fig. 7. Second, the DJF IQR for these cells is greater than 0.3 $mm\,d^{-1}$, indicating that 25 % of the GCMs would show trend modifications by BC in excess of approximately 0.3 $mm\,d^{-1}$ (the median plus 1/2 of the IQR), which is on the order of the observed trend in Fig. 7. This latter point makes clear the importance in using an ensemble of GCMs rather than one or a few, since the regions of enhancement/reduction of trend are not coherent across different models and the effect diminishes when combined into an ensemble.

Perhaps more importantly, in Fig. 6, some areas where the BC process appears (in the median) to produce drier conditions than the raw GCM are also areas where the observed difference between the 1976–2005 and 1916–1945 periods is considerably lower than the GCMs simulate. One example is the central portion of the East coast, where Figs. 4 and 5 show half the models simulating wettening DJF conditions between 1976–2005 and 1916–1945, in distinct contrast to the drying trend in the observations.

This raises the question of whether the change induced by BC in the precipitation sensitivity (or trend) between the two periods degrades or improves the

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correspondence between simulated and observed trends. In terms of the link between the trend modification and variance, this is equivalent to asking if models with variances that are too large tend to have trends that are too large, and vice versa. The index described above is used to illustrate this for each GCM for DJF in Fig. 8. Values in blue (negative values) show where the effect of the BC results in an improved representation of the observed difference in precipitation between the two periods, and red (positive values) indicate a degraded precipitation trend due to BC. It is evident that over the entire domain, for each GCM there are areas of improved and areas of degraded precipitation trend representation due to BC. Regions with improved or degraded skill vary from GCM to GCM, with no apparent geographical consistency. In sum, the errors in an individual model's variance appear unrelated to the errors in the model's trend.

Figure 9 summarizes the results for the ensemble in Fig. 8 and the similar ensemble for JJA. The median index values (left panels) tend to lie close to zero, and neither degraded (index > 0) or improved (index < 0) values dominate the picture for either DJF or JJA. The center panels highlight regions where 75 % of the GCMs show a degraded change in precipitation (relative to the observed change) due to the BC process. These cases constitute 2.8 % of the grid cells for DJF and 8.3 % of the grid cells for JJA. The right panels show the grid cells where 75 % of the GCMs show improved correspondence with the observed change after BC. These cover 15.8 % and 7.3 % of the domain for DJF and JJA, respectively.

The analysis was repeated using 1946–1975 compared to 1916–1945 to ensure that the results obtained were not overly dependent on the single selected period. The results of the analysis with this second period are shown in Fig. 10, where 75 % of the GCMs show a degraded change in precipitation sensitivity following BC in 7.5 % of the grid cells for DJF and 10 % for JJA. In contrast, 15.9 % of the grid cells show improved correspondence to observed trends for DJF precipitation, and 5.1 % show improved precipitation trends for JJA.

This suggests that with an ensemble of 12 GCMs as used in this effort the BC produces no consistent improvement or degradation in the simulated GCM precipitation

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change. While the effect of BC on the trend can be significant, it tends as often as not to bring GCM simulated trends closer to observed trends for the periods used in this study. However, there are isolated locations where the trend appears to be degraded for most model simulations, which could be of particular interest for impacts studies. One such case if the North Central portion of the domain, where Figs. 9 and 10 (center panels) both show grid cells for which JJA precipitation trends are degraded for 75 % of the GCM simulations by the BC process. For these locations, it may be beneficial to retain the raw GCM simulated trend during impacts analysis studies. Conversely, in Figs. 9 and 10 (right panels) there are some grid cells in the Northwest where DJF precipitation trends are improved by BC for most of the GCM simulations.

One of the driving motivations for much downscaling is the investigation of regional and local hydrological impacts of climate change (Fowler et al., 2007). Since the runoff response to changing precipitation is highly non-linear (Wigley and Jones, 1985), changes in precipitation are amplified in their convolution to runoff changes. This emphasizes the importance in ensuring that the projected precipitation trends not be degraded during the BC process, since the implications would be for even greater biases in projected runoff changes.

4 Summary and conclusions

Quantile mapping bias correction has been shown to modify the projected changes, or trends, produced by climate models. This is of critical concern regarding precipitation projections, where changes to the raw climate model output can have significant impacts on the implications for water supply and management in the face of climate change. The resulting discrepancy between the raw climate model output and bias corrected output leaves some ambiguity as to whether the bias correction should be modified to preserve the original climate model simulated changes.

We examined the historical changes in daily mean precipitation simulated by 12 climate models across the conterminous United States. We compared the differences

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between precipitation for two 30-yr periods: 1916–1945 and 1976–2005 for all GCMs, both before and after a quantile mapping bias correction, and gridded observed precipitation. We consider winter and summer precipitation separately. We repeated the process comparing 1916–1945 and 1946–1975.

We found that the bias correction did produce different precipitation changes from the raw GCM output, with a wettening effect in some locations and a drying effect in others. While there was some spatial consistency in regions showing a tendency for bias correction to make the projections wetter or drier, the skill, measured as a correspondence to observed changes, was more variable, with different GCMs responding to bias correction differently. Taken as an ensemble, the bias correction had no coherent, overwhelming negative or positive effect on the correspondence of the simulated to observed precipitation changes between periods. Reliance on a single GCM or a small sample of GCMs however could, for some regions, result in a degraded simulated trend in precipitation due to bias correction.

Based on these results, it does not appear that there is a clear advantage to either preserving the raw GCM-simulated trend in precipitation during bias correction or allowing the trend to be modified by the process. In most locations, as long as a reasonable ensemble size is used, even though the trend in seasonal precipitation may be modified in the process, it may be as likely as not to be beneficial to do so.

These findings are limited to the extent of this study, namely seasonal mean precipitation for 30-yr observed periods. Since changes in the magnitude of extreme precipitation events are of important for assessing many impacts to society, future efforts will examine the effect of quantile mapping bias correction on trends in extreme events. Furthermore, the bias correction was performed at a 1° spatial scale, so that the observations are comparable to the scale of the GCMs. At finer scales, the biases between interpolated GCM output and observations would be expected to be much more heterogeneous, and the impact of quantile mapping bias correction at finer scales could be quite different from that found here, though employing quantile mapping to downscale to fine scales has been found to be problematic (Maraun, 2013).

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Table 1. Climate models used in this study.

	Modeling Center	Model Name
1	Commonwealth Scientific and Industrial Research Organization (CSIRO) and Bureau of Meteorology (BOM), Australia	ACCESS1.0
2	Canadian Centre for Climate Modelling and Analysis	CanESM2
3	National Center for Atmospheric Research	CCSM4
4	Centre National de Recherches Météorologiques/Centre Européen de Recherche et Formation Avancée en Calcul Scientifique	CNRM-CM5
5	Commonwealth Scientific and Industrial Research Organization in collaboration with Queensland Climate Change Centre of Excellence	CSIRO-Mk3.6.0
6	NOAA Geophysical Fluid Dynamics Laboratory	GFDL-CM3
7	NASA Goddard Institute for Space Studies	GISS-E2-R
8	Institute for Numerical Mathematics	INM-CM4
9	Institut Pierre-Simon Laplace	IPSL-CM5A-MR
10	Max-Planck-Institut für Meteorologie (Max Planck Institute for Meteorology)	MPI-ESM-LR
11	Meteorological Research Institute	MRI-CGCM3
12	Norwegian Climate Centre	NorESM1-M

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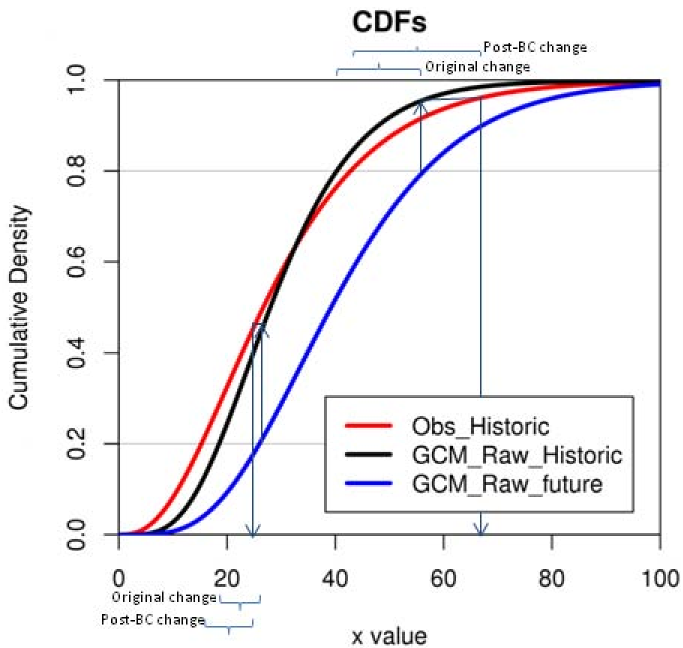

Fig. 1. Cumulative distribution functions for a synthetic demonstration set of observed, GCM simulated historic, and GCM projected future precipitation data.

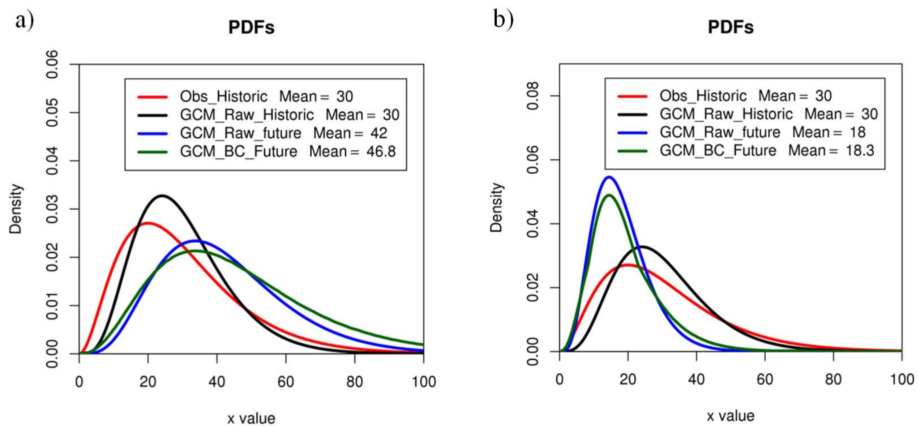

Fig. 2. Probability Density Functions for the same synthetic data in Fig. 1, but including the post-bias correction GCM future projection.

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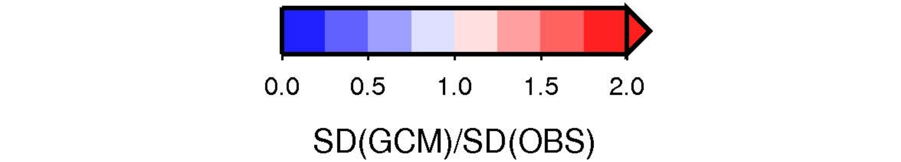

Fig. 3. Ensemble median of the ratio of the standard deviation (SD) for the GCMs to the SD of the observations for daily precipitation during DJF and JJA.

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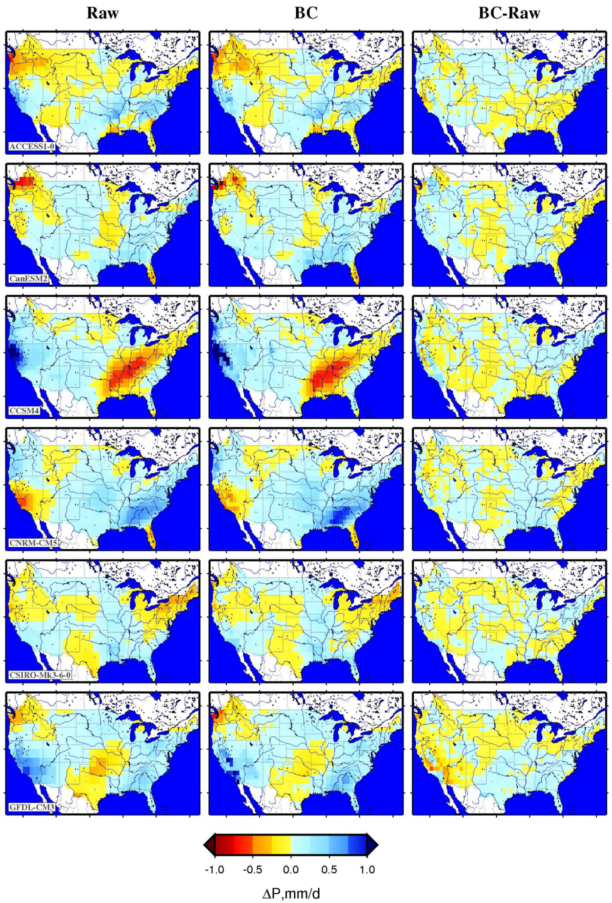

Fig. 4. For GCMs 1–6, the change in mean DJF precipitation between 1916–1945 and 1976–2005 for the raw GCM output (left column) and bias corrected GCM output (center); the difference between the two is in the right column.

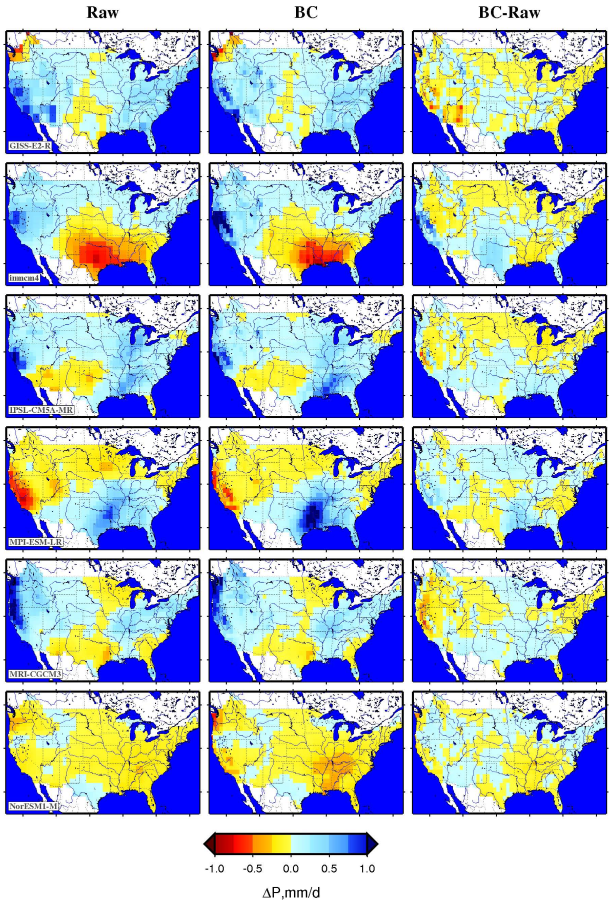

Fig. 5. Same as Fig. 4 but for GCMs 7–12.

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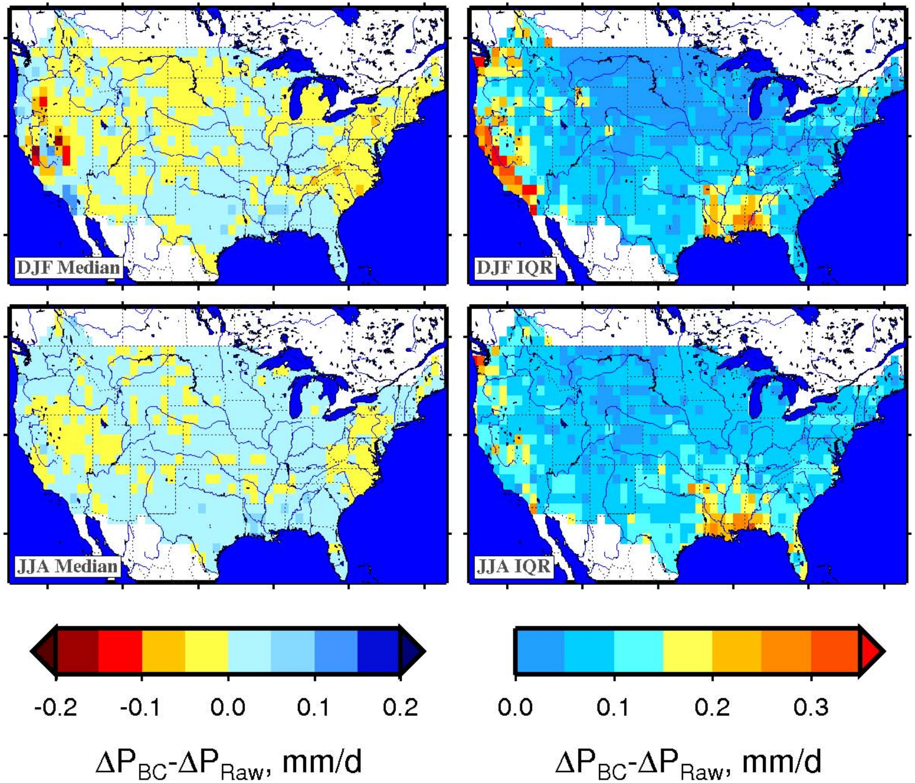

Fig. 6. Ensemble median difference between the BC and Raw differences in precipitation between 1976–2005 and 1916–1945 for DJF (top row) and JJA (bottom row). Right column is the interquartile range (IQR), defined as the 75th percentile minus the 25th percentile.

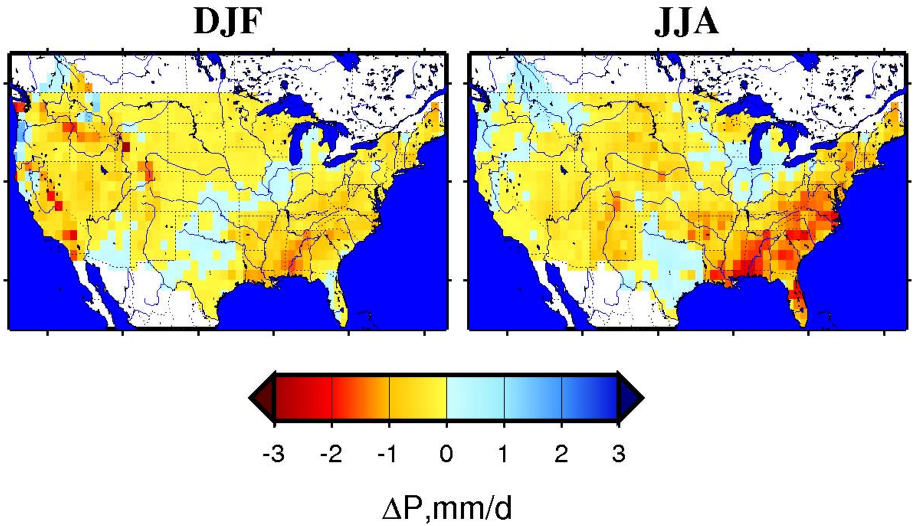

Fig. 7. Difference between seasonal mean precipitation of 1976–2005 and 1916–1945.

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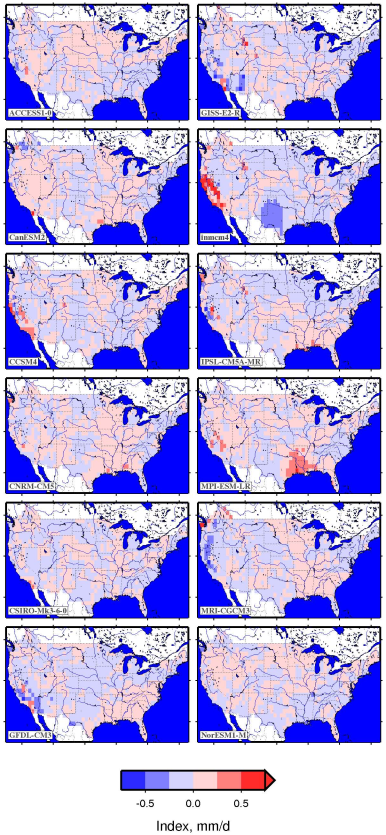

Fig. 8. For DJF, the index (described in the text) values for each GCM.

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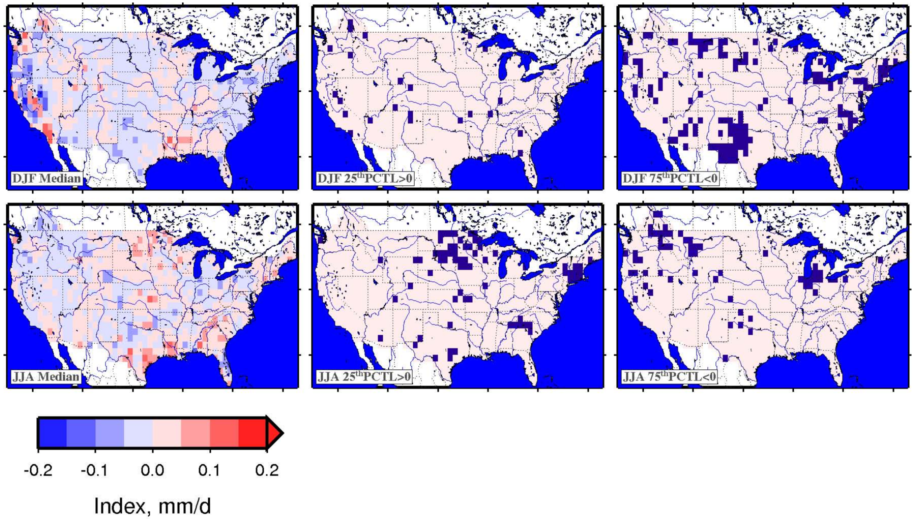

Fig. 9. For DJF and JJA, the ensemble median index value (left panels), the locations of grid cells (dark rectangles) where the 25th percentile index value exceeds 0 (center panels), and the grid cells where the 75th percentile value is less than 0.

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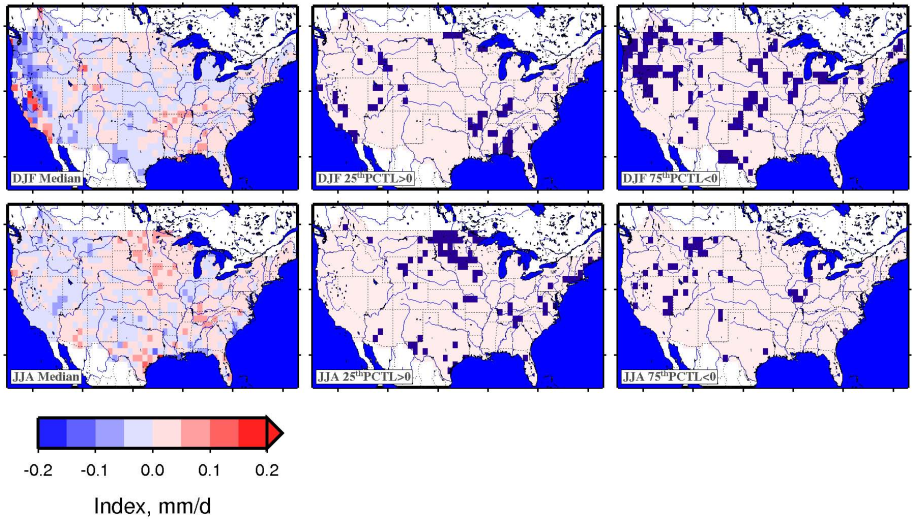

Fig. 10. Same as Fig. 9 but for comparing the 1946–1975 period to 1916–1945.

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