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On bias correction in drought frequency analysis based on climate models

Yog Aryal[1] **· Jianting Zhu**[1]

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Abstract Assessment of future drought characteristics based on climate models is difficult as climate models usually have bias in simulating precipitation frequency and intensity. In this study, we examine the significance of bias correction in the context of drought frequency and scenario analysis using output from climate models. In particular, we use three bias correction techniques with different emphases and complexities to investigate how they affect the results of drought frequency and severity based on climate models. The characteristics of drought are investigated using regional climate model (RCM) output from the North American Regional Climate Change Assessment Program (NARCCAP). The Standardized Precipitation Index (SPI) is used to compare and forecast drought characteristics at different timescales. Systematic biases in the RCM precipitation output are corrected against the National Centers for Environmental Prediction (NCEP) North American Regional Reanalysis (NARR) data and the bias-corrected RCM historical simulations. Preserving mean and standard deviation of NARR precipitation is essential in drought frequency analysis. The results demonstrate that bias correction significantly decreases the RCM errors in reproducing drought frequency derived from the NARR data. Different timescales of input precipitation in the bias corrections show similar results. The relative changes in drought frequency in future scenario compared to historical scenario are similar whether both scenarios are bias corrected or both are not bias corrected.

1 Introduction

Recent years have witnessed large socioeconomic consequences of drought including direct losses in agriculture production to ripple effects such as loss of jobs. Droughts, unlike other

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✉ Jianting Zhu
jzhu5@uwyo.edu

[1] Department of Civil and Architectural Engineering, University of Wyoming, Laramie, WY 82071, USA

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natural disasters, evolve slowly over time and their impacts generally span a long period of time. Since the definition varies among the interested groups, it is difficult to devise a universal quantitative drought index. Comprehensive reviews of limitations and applications of various drought indices, either using precipitation as a single variable or in combination with other variables, used in drought monitoring are given in Mishra and Singh (2010). Among many drought indices, the Standardized Precipitation Index (SPI) developed by McKee et al. (1993) has been widely used in drought characterization across the globe (Edwards and McKee 1997; Natle and Gan 2003). Vicente-Serrano et al. (2010) formulated new drought index called the Standardized Precipitation Evapotranspiration Index (SPEI) which includes evapotranspiration (ET) to calculate water balance, which includes more variables and as a result large source of uncertainties are introduced based on climate model results. Precipitation is a major source of moisture supply and ET during drought, although their relationships are complex. As a trade-off, we assume that the precipitation anomaly can reasonably show drought scenario although the SPI has a main limitation that it does not include ET (Zarch et al. 2015). Calculation of SPI is relatively simple (uses precipitation as only input variable), spatially invariable in interpretation as it is relative to a regions own climatology, and in any timescale (e.g., 3 months for soil moisture anomaly to years for water storage). Therefore, we use the SPI as the drought index.

Although climate models are important tools for analyzing past and future climate characteristics, results show a large degree of uncertainty for key hydrological variables (Xu 1999). Climate model precipitation simulations are biased due to the incomplete representation of atmospheric physics and generalization of the natural heterogeneity of the climate system occurring at finer spatial and temporal scale (Xu and Singh 2004; Wood et al. 2004; Li et al. 2010; Rosenberg et al. 2010). These biases in climate model outputs should be corrected to improve the realism of regional climate model (RCM) based on statistical properties of observation from some baseline period. Johnson and Sharma (2015) found significant differences between droughts assessments using raw global circulation model (GCM) simulations and using bias-corrected sequences. Osuch et al. (2015) showed that the spatial pattern of the trend depends on the bias correction, the climate model, and the time scale considered. There are several reviews of existing bias correction methods and their advantages and disadvantages (e.g., Wood et al. 2002; Li et al. 2010; Johnson and Sharma 2011).

Because of very complex nature of climate model biases, results obtained from same bias correction technique in input variable (such as precipitation) shows varying accuracy for different purpose such as drought and flood frequency analysis. Several efforts have been made to analyze projected changes in drought scenario using climate models. Sheffield and Wood (2008) analyzed future global drought scenario based on soil moisture anomaly at different timescales. Climate models' ability to reproduce drought statistics was analyzed and projected changes were reported by Wehner and Santer (2011). Jeong et al. (2014) analyzed projected changes in drought frequency and severity. However, very little effort has been made to quantify biases in climate model outputs and significance of bias correction for future scenario analysis.

This study is to answer two main scientific questions related to bias correction and drought analysis based on climate model output: (1) How should bias correction technique be properly chosen in drought frequency analysis, and (2) How would bias correction affect future drought frequency results based on climate models? The first objective is to examine the effectiveness and impact of the bias correction in analyzing drought frequency and severity based on output from RCMs. We compare several bias correction techniques with different emphases and analyze important features that should be preserved in analyzing drought characteristics. The second objective is to examine the future scenario drought frequency and severity compared with current scenario based on output from climate models in representative locations across the USA. We then investigate how bias correction will affect the results.

In general, the SPI is precipitation deficit at any place compared to its long-term average climatology. We select bias correction techniques that basically correct mean and standard deviation of the climate model precipitation against reanalysis (or observation). We also examine whether correcting higher order moments (such as autocorrelation and cumulative distribution as discussed later under "Methods") would improve the temporal clustering (or scatter) of climate model precipitation compared with observation and hence reduce the biases in drought frequency. Three-, 6-, and 12-month drought frequencies are calculated from RCMs' bias-corrected historical scenario data and effectiveness of bias correction is analyzed. Impact of future climate on drought frequency and severity is analyzed by comparing RCMs' future scenario with historical scenario drought.

2 Methods

We mainly use the two precipitation data sources. The National Centers for Environmental Prediction (NCEP) North American Regional Reanalysis (NARR) provides observed gauge precipitation data assimilated at 32-km spatial resolution and temporal resolution of 3 h. The NARR has effectively assimilated gridded model precipitation quite similar to the input gauge precipitation (Mesinger et al. 2006). These data are available at temporal span of 1979 to 2013 and are considered as a good representation of historical weather at the grid scale because they are constrained to the historical observations (Zhu et al. 2013). For climate models, the North American Regional Climate Change Assessment Program (NARCCAP) provides grid-scale precipitation at 50-km spatial and 3-h temporal resolutions from many combinations of GCMs and RCMs for historical (1971–1999) and future (2041–2070) scenarios. In this study we use three different combinations of two RCMs and two GCMs to give some general idea of effect in term of boundary conditions (as provided by RCMs) and climate model parameterizations (as provided by GCMs). While other models combinations from the NARCCAP can also be easily used, comprehensive study of all NARCCAP models is beyond the scope of this study. But we want to emphasize that the designed approach in this study can be easily used in any other climate models. We average nine NARCCAP grid cells in each location to estimate average precipitation for that location since drought characteristics are generally analyzed in spatial context rather than point estimate. The NARR grid cells covering the same spatial extent as the nine NARCCAP grids are averaged to calculate average NARR precipitation.

Based on these two data sources, the general approaches of this study are described as follows. We calculate the SPI in 3-, 6-, and 12-month time scales from the NARR precipitation time series and RCMs' historical scenario time series using the NARR data and the bias-corrected historic runs from the RCMs as climatic baseline data. Drought frequency is calculated as the percentage of time when SPI ≤ 0 and severe drought frequency as SPI ≤ -1.5. Climate model bias is analyzed by comparing drought frequency from the NARR and RCMs' historical scenario simulations. Biases in RCMs monthly total precipitation are corrected against NARR precipitation time series by three approaches: (1) monthly bias correction (MBC), (2) nested bias correction (NBC), and (3) equidistance quantile mapping (EQM), and the same correction is applied for the RCMs' future scenario precipitation. From the monthly precipitation output, we perform bias corrections in two different ways: (1)

correcting bias separately for each month of the year and (2) correcting bias for the entire monthly time series data in one step without separating month of the year. We perform later approach particularly to increase sample size in analysis that may increase the performance of bias correction technique. We then examine how these two different bias correction approaches may affect the results of drought frequency and severity analysis.

We investigate and compare three widely used bias correction techniques with different emphases and complexities, including the MBC (Johnson and Sharma 2011), the NBC (Johnson and Sharma 2011), and the EQM (Li et al. 2010) to correct the RCMs' biases in reproducing different timescale drought frequency and severity. Calculation methodology and formulations of these three bias correction techniques are given in the Supplementary Materials (1, 2, and 3). These bias correction methods generally correct the statistics of RCM output precipitation against the NARR data and apply the same correction to the RCM future-predicted precipitation.

In the MBC method, the mean and standard deviation of the RCM precipitation are corrected according to the NARR statistics and the same correction is applied for the future time series. While correcting future time series, it is standardized by RCM historical statistics and imposed reanalysis statistics. Therefore, the RCM future precipitation does not have the same mean and standard deviation as the NARR data. In the NBC method, the mean, standard deviation and one-lag autocorrelations simultaneously at monthly and annual time scales are corrected against the NARR. The EQM technique corrects distribution of monthly precipitation from the RCM historical simulations from that of the NARR data.

After the bias correction of precipitation time series, we then calculate the SPI. To calculate the SPI of any time series of precipitation, we need to first define the climatological baseline data series. In this study, the climatological baseline data series is from the NARR reanalysis data. For comparison, we also perform SPI analysis using bias-corrected RCM historical runs as the baseline data. For a given month of the year and timescale of drought (i.e., 3-, 6-, or 12-month), the monthly precipitation data series from the NARR reanalysis data is summed over the timescale of interest using moving window of that timescale to generate a new series. We then prepare the precipitation time series for each month and for each timescale. The gamma distribution is then used to fit the generated data set (Thom 1966). The maximum likelihood solutions are used to estimate the parameters in the gamma distribution as suggested by Edwards and McKee (1997). These parameters are estimated for each month of the year and the given timescale of interest. The resulting parameters from the NARR data are used to find the cumulative probability of the precipitation time series of interest.

The timescale of drought is selected based on the concern for precipitation deficit that affects the particular type of usable water sources. For example, soil moisture conditions respond to relatively short timescale (1–3 months) precipitation anomaly whereas hydrological variables related to stream flow, groundwater, and reservoirs respond to longer term (12 months or longer) precipitation anomalies (World Meteorological Organization 2012). Guttman (1999) suggested the 1- to 24-month SPI as the best practical range of applications. We calculate the SPI for the 3-month (short-term drought), 6-month (medium- term), and 12-month (long-term) timescales for all months in the time series of precipitation total (3-, 6-, and 12-month). Any month with SPI ≤ 0 and SPI ≤ -1.5 is designated as dry and severely dry month, respectively. Drought (severe drought) frequency in any time series is calculated as the ratio of number of months with SPI ≤ 0 (SPI ≤ -1.5) to the total number of months.

We use a simple measure of error (E) of the drought frequency defined as follows to evaluate the model efficiency in capturing frequency of particular drought category,

$$E = \text{Drought Frequency from NARR} - \text{Drought Frenquency from RCM} \tag{1}$$

Therefore, a positive E means that the RCM simulates too wet conditions while a negative E denotes too dry conditions from the RCM simulations compared to the NARR data.

Previous studies have analyzed spatial variability of climate models' capability in capturing hydrological extremes. Zhu et al. (2013) and Zhu (2013) compared Intensity-Duration-Frequency (IDF) curves from the NARCCAP models with those from the NARR reanalysis and analyzed the future scenarios in several locations across the USA. From the Principal Component (PC) analysis on the gridded value of Palmer Drought Severity Index (PDSI), Karl and Koscielny (1982) delineated nine readily identifiable pattern of drought across the contiguous USA. Diaz (1983) grouped the States into nine regions and these classifications are still being used by the National Climate Data Center to analyze climate anomalies (Karl and Koss 1984). In this study, we analyze the drought characteristics in some representative locations from these nine regions. Figure 1a shows the geographical locations of representative locations of this study. Drought frequency analysis from both the RCMs' historical and future scenario simulations is performed. Future changes in drought frequency are calculated and discussed based on the RCMs' future scenario simulations for these nine locations.

3 Results

Figure 1 shows the errors in the drought frequency at different timescale for the historical simulations of all the three RCMs without bias corrections. Observed drought frequencies from the NARR are shown in the Supplementary Material Table S4. Error in drought frequency is calculated based on Eq. (1). The results in Fig. 1 also demonstrate regional variations in climate model's ability in simulating drought frequency. Out of the three RCMs we investigated, the CRCM_CGCM3 simulate too wet conditions and the other two models

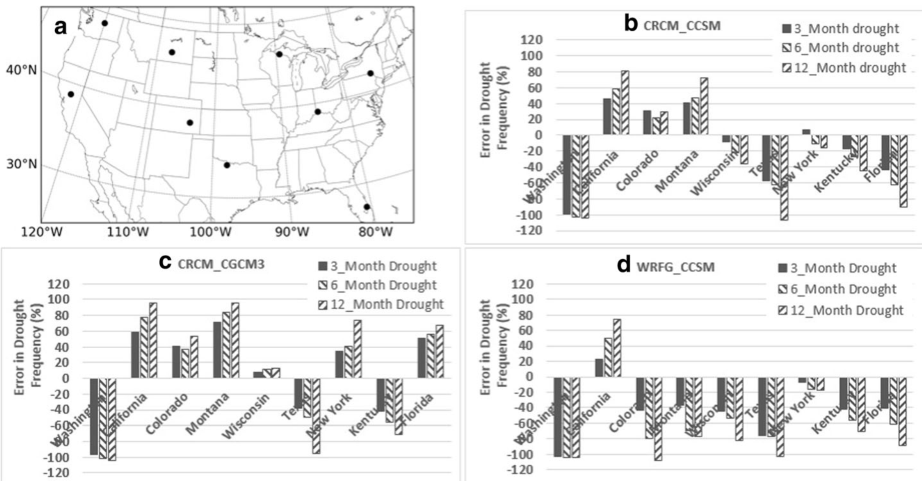

Fig. 1 Errors in drought frequency at different locations for different timescale drought frequency before bias corrections. **a** Locations of the study (*black dots*); **b** CRCM_CCSM; **c** CRCM_CGCM3; and **d** WRFG_CCSM

simulate too dry conditions. All results shown in Fig. 1 highlight significant bias of climate models in simulating drought frequency. The relative errors in drought frequency could be greater than 100%. Quantitatively, this large error could mean that a 0.49 observed drought frequency may be simulated as 1.0 showing large 104% [= (1.0 − 0.49)/0.49] relative error.

Figure 2 shows the remaining biases in drought frequency after bias correction using the MBC, NBC, and EQM, respectively. There is no significant difference in the errors in drought frequency from the three bias correction techniques (i.e., MBC, NBC, and EQM). All three bias correction techniques correct the statistics of RCM precipitation. However, scatter in precipitation time series was not improved for any months and in any location. In general, the errors in the drought frequency have been reduced significantly after bias correction for all locations and timescales. For example, the largest error in drought frequency before bias

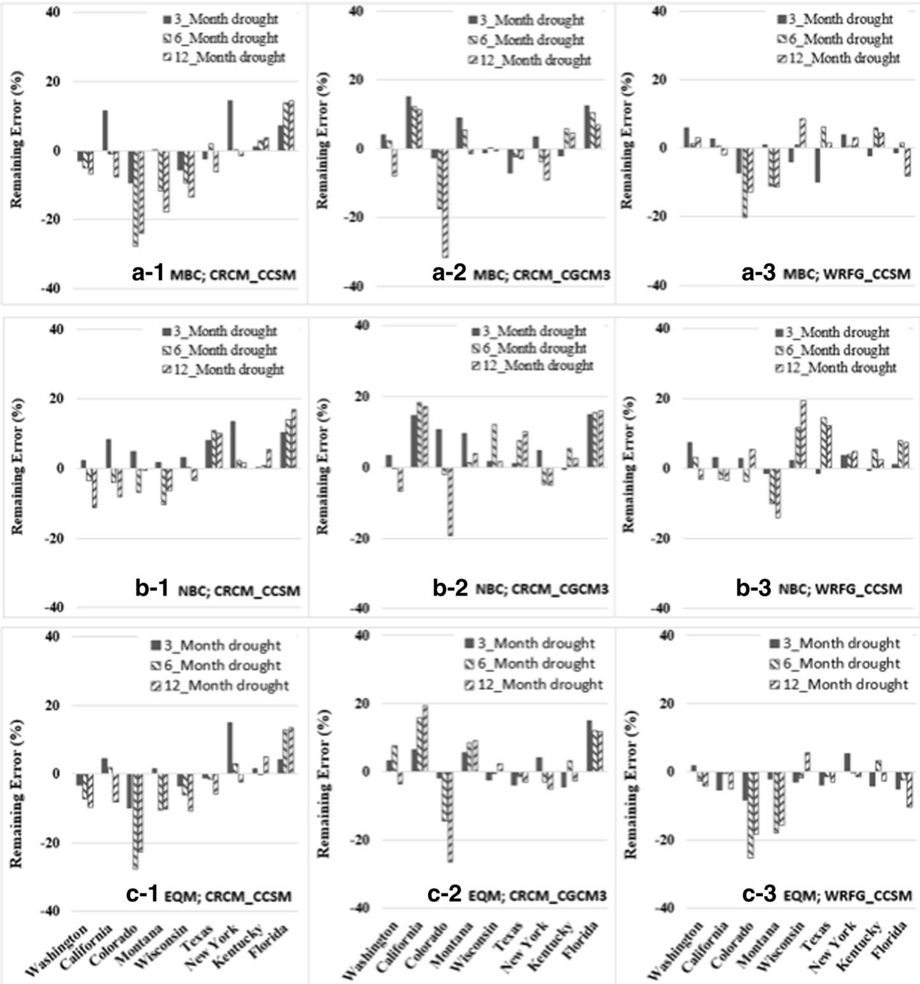

Fig. 2 Remaining errors in drought frequency after bias correction in precipitation separating monthly distribution: **a** MBC (*a-1*, CRCM_CCSM; *a-2*, CRCM_CGCM3; and *a-3*, WRFG_CCSM); **b** NBC (*b-1*, CRCM_CCSM; *b-2*, CRCM_CGCM3; and *b-3*, RFG_CCSM), and **c** EQM (*c-1*, CRCM_CCSM; *c-2*, CRCM_CGCM3; and *c-3*, WRFG_CCSM)

corrections is 107% which is reduced to 6.29% after bias corrections (Texas, 12-month drought, CRCM_CCSM, Fig. 2). Remaining error in different timescale drought frequency after the bias correction varies from −31% (under estimation) to +20% (over estimation), which is in a much smaller range than the −107 to +95% range before the correction. Therefore, the bias correction can improve RCMs' ability to reproduce drought frequency, we move to analyze changes in future drought scenarios.

Note that all the bias-corrected results presented earlier have been generated by correcting bias in the precipitation time series for each month of the year. As we discussed earlier, we also perform bias correction using the entire monthly time series of precipitation data rather than using the time series based on the month of the year. In other words, we need to apply the bias corrections only once. In all cases, the same three bias correction methods (i.e., MBC, NBC, and EQM) are used and results from MBC are shown in Fig. 3. Similar results from the NBC and EQM are presented in the Supplementary Material in Table S1. No detectable differences are observed in reducing the errors in the drought frequency (remaining biases about ±22%) by using the two different bias correction maneuvers.

As shown in Fig. 2, climate model errors in capturing the drought frequency and severity show regional variations. One model performing well at one location may not perform well at other locations in reproducing the same climate variable (drought frequency in this study). We choose a RCM whose historical simulations have smallest errors in producing the drought frequency (the average errors in 3-, 6-, and 12-month drought frequency) from the NARR data for a particular location as the best performing model among three RCMs for that location. Then we analyze possible changes in the drought characteristics based on the future scenario simulations from this best performing RCM. In general, WRFG_CCSM is found to be better for coastal regions and for central regions CRCM_CGCM3 is better in northern part and CRCM_CCSM in southern part.

We have analyzed the effectiveness of three bias correction techniques with different complexities. We have shown that the relatively simple MBC, which correct the bias in both the mean and standard deviation, produces similar results compared to more sophisticated methods. Therefore, the MBC technique is chosen in the bias correction in the subsequent analysis of future changes in drought frequency. In Table 1 we present some results of projected drought frequencies and changes in the future scenario compared with historical scenario. The results in Table 1 are obtained from the bias correction in the entire time series (without separating monthly distribution) particularly to increase sample size in analysis. The results from bias correction after separating to monthly distribution are shown in the Supplementary Material Table S3. After bias correction, we separate into monthly series again then calculate drought frequency based on monthly distribution. Table 1a shows percentage changes in the drought frequency from the future simulations (2040–2070) of the RCMs compared with the historical simulations (1970–2000) for all locations and all timescales. Note that the precipitation time series input from both the historical and future simulations is bias corrected using the MBC. Regardless of their ability to simulate drought statistics in climatological base period, all RCMs analyzed here project significant changes in the drought frequency and severity in all locations over the middle of twenty-first century (2040–2070). The results suggest increases in future drought frequency of all timescales in California, Texas, Kentucky, and Florida. Large percentage increase is shown in Florida where about 51% increase in all timescale drought frequency is predicted. Smaller percentage changes in drought frequency are predicted in Texas and Kentucky on the order of about 5 and 10% on average for all timescales. Future drought frequency is shown to decrease over Colorado, Montana, and

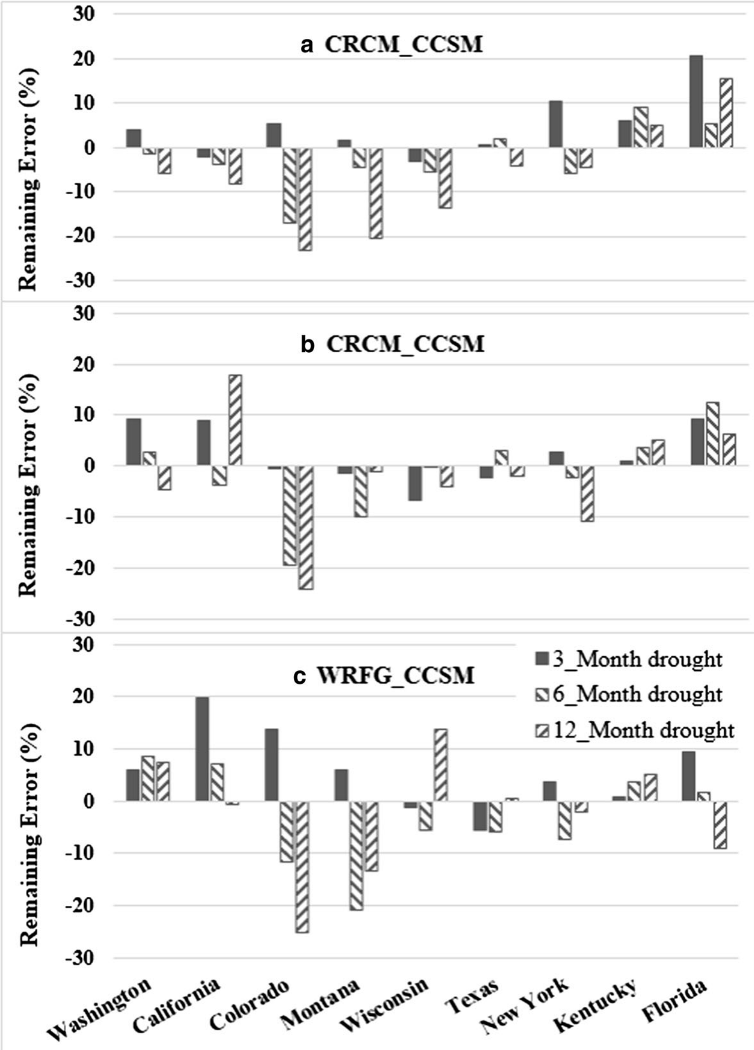

Fig. 3 Remaining errors in drought frequency after bias correction in precipitation using MBC technique without separating monthly distribution

Wisconsin for all timescales. Large percentage decrease is predicted over Wisconsin where about 40% decrease on average for all timescales. The projected changes in precipitation with and without bias correction are shown in Table S5 a-b in the Supplementary Material and are generally consistent with the projected changes in drought frequency. However, it is difficult to infer changes in drought index from changes in total precipitation. In general, nature of changes in severe drought frequency is similar to the changes in drought frequency for all timescale in all locations but the magnitude of changes is larger. For example, very large percentage (about 725%) increase in 12-month severe drought frequency is predicted in Florida where 12-month severe drought frequency changes from 0.04 to 0.31. It should be noted that we fit gamma distribution in the baseline data for SPI calculation as well as for bias

Table 1 Projected drought frequencies and changes in the future scenario

(a) Percentage change in future drought frequency, bias corrected by the monthly bias correction (MBC)

Location	Drought frequency			Severe drought frequency		
	3-month	6-month	12-month	3-month	6-month	12-month
Washington	1.695	−7.078	−15.254	3.030	70.000	42.857
California	12.567	10.764	8.955	110.013	105.263	266.667
Colorado	−2.564	−5.667	−9.195	0.000	−27.273	−63.636
Montana	−13.187	−17.113	−21.809	−13.889	−10.526	−32.609
Wisconsin	−30.978	−44.402	−57.062	−29.412	−33.333	−66.667
Texas	13.485	12.134	20.000	79.782	169.565	600.000
New York	−3.158	2.177	−11.834	0.000	40.000	−10.526
Kentucky	4.688	3.730	1.053	39.286	123.810	176.923
Florida	42.500	48.812	50.711	318.750	584.615	728.571

(b) Projected future drought frequency (assuming NARR data as baseline)

Location	3-month drought		6-month drought		12-month drought	
	Without correction	With correction	Without correction	With correction	Without correction	With correction
Washington	1.000	0.471	1.000	0.451	1.000	0.402
California	0.466	0.540	0.359	0.559	0.225	0.587
Colorado	0.657	0.497	0.763	0.475	0.954	0.424
Montana	0.152	0.414	0.042	0.385	0.008	0.394
Wisconsin	0.322	0.332	0.216	0.264	0.166	0.204
Texas	0.757	0.542	0.871	0.554	0.954	0.611
New York	0.510	0.482	0.520	0.478	0.488	0.399
Kentucky	0.631	0.526	0.665	0.520	0.745	0.515
Florida	0.759	0.746	0.889	0.773	1.000	0.853

(c) Projected future drought frequency (assuming corrected NARCCAP data as baseline)

Location	3-month drought		6-month drought		12-month drought	
	Without correction	With correction	Without correction	With correction	Without correction	With correction
Washington	1.000	0.500	1.000	0.465	1.000	0.422
California	0.456	0.562	0.341	0.548	0.208	0.551
Colorado	0.651	0.470	0.750	0.468	0.951	0.454
Montana	0.148	0.422	0.049	0.403	0.008	0.401
Wisconsin	0.326	0.360	0.216	0.285	0.177	0.218
Texas	0.813	0.565	0.865	0.567	0.966	0.608
New York	0.505	0.487	0.531	0.492	0.557	0.433
Kentucky	0.654	0.546	0.695	0.532	0.755	0.500
Florida	0.771	0.750	0.878	0.785	1.000	0.823

(d) Percent changes in future drought frequency without bias correction in both historic and future scenario versus with bias correction

Location	3-month drought		6-month drought		12-month drought	
	Before correction	After correction	Before correction	After correction	Before correction	After correction
Washington	0.262	1.695	0.000	−7.078	0.000	−15.254
California	21.918	12.567	42.471	10.764	68.000	8.955
Colorado	−3.462	−2.564	1.350	−5.667	11.250	−9.195
Montana	0.000	−13.187	−44.421	−17.113	−62.500	−21.809
Wisconsin	−26.786	−30.978	−48.726	−44.402	−59.477	−57.062
Texas	2.847	13.485	6.001	12.134	−3.784	20.000
New York	−8.019	−3.158	−4.399	2.177	−10.784	−11.834
Kentucky	5.702	4.688	1.213	3.730	−2.456	1.053
Florida	4.317	42.500	4.484	48.812	1.359	50.711

correction. This very large increase in 12-month severe drought frequency is probably from the discrepancy in the tail of the gamma distribution fit uncertainty due to limited length of precipitation data (only 30 years)

To examine the effects of bias correction on the prediction of relative change in future drought frequency we also compare the change in drought frequency in the future when both historical and future scenario precipitation time series are bias corrected (Corrected) with that when both precipitation time series are not corrected against systematic biases (Raw). We calculate the change in frequency without bias correction = Raw future − Raw historical, and the change in frequency with bias correction = Corrected future − Corrected historical. Table 1b shows the comparison of the simulated future drought frequency results when the RCM model precipitations are bias corrected with those when the simulated precipitations are not bias corrected. We also analyze the future drought frequencies with and without bias correction assuming bias-corrected NARCCAP RCM historical time series as baseline data. As shown in Table 1c, results are very consistent in both cases assuming NARCCAP RCMs and NARR data as baseline data. It is not surprising that the PSI results based on the bias-corrected RCM historic simulations is similar to that based on the reanalysis data, since after bias correction the RCM historic precipitation should be statistically similar to the NARR reanalysis precipitation. Very large drought frequencies simulated by RCM in future scenario are reduced after bias correction as shown in Table 1b-c. Similar effects of bias correction are also reported from other studies (e.g., Johnson and Sharma 2011; Osuch et al. 2015). For most cases, the drought frequencies with and without bias corrections are very different in terms of the actual drought frequency. However, if we only look at the relative changes in drought frequency (i.e., future drought frequency − historical drought frequency), we may expect that the differences are much smaller. Table 1d shows the relative changes in future drought frequency with and without bias corrections. The differences in these two cases are now much smaller. With few exceptions, the changes in drought frequency with and without bias corrections show similar trend at same locations (i.e., either positive change meaning increase in future drought frequency or negative change meaning decrease).

4 Discussion

As shown in Table 1, there are significant differences in future drought frequency when RCM output is bias corrected or not. Bias correction is important in simulating and analyzing future drought scenarios. However, climate models data without bias correction might be reasonable to be used directly if our goal is only to analyze future changes in drought frequency relative to historical drought frequency. Since both historical simulations and future scenario simulations from a same RCM may include similar biases, they may cancel out if we are only concerned about their relative differences in the drought frequency.

In Table 2 we present the ratio (r) of the projected change in future scenario drought frequency to the remaining bias after correction in drought frequency in historical scenario for all timescales at all locations. The ratio, r, is defined as follows,

$$r = \left| \frac{\text{Corrected future} - \text{Corrected Historical}}{\text{Corrected historical} - \text{Reanalysis}} \right| \tag{2}$$

As discussed earlier and shown in Fig. 2, errors in reproducing drought frequency are significantly reduced after correcting systematic biases in the RCM precipitation output.

Table 2 Ratio of projected change in future scenario drought frequency to the remaining bias in historical drought frequency

Location	*r*		
	3-month drought	6-month drought	12-month drought
Washington	0.27	5.72	5.00
California	4.70	15.86	4.49
Colorado	0.38	0.34	0.81
Montana	1.32	2.97	14.30
Wisconsin	26.65	1610.53	102.25
Texas	5.76	6.32	3.38
New York	0.81	4.10	3.85
Kentucky	5.17	1.28	0.29
Florida	32.66	30.91	6.76

However, remaining errors after bias correction are large enough that cannot be underestimated for further analysis in some cases. Table 2 shows the relative significance of projected changes in drought frequency compared to the RCMs' ability (after bias corrections) to capture observed drought frequency in historical scenario. In some locations r is below 1 indicating that the projected changes for future scenario are not significant compared to the remaining biases (after bias correction). For instance, r for 3-month drought frequency in Washington and 12-month drought frequency in Kentucky are well below 1, which means the climate model biases in reproducing observations are significantly larger compared to the projected changes in future scenario. On the other hand, large r value in the projected changes in drought frequency in Wisconsin for all time scales illustrates that the projected changes are robust compared to climate model biases. This shows regional variations in the climate model efficiency, which deserves further analysis of local and regional climate system dynamics and their formulations in climate models. Future projections based on the RCMs should be interpreted with caution considering climate models' ability in reproducing the observed drought frequencies in the past.

All RCM historical simulations show larger errors for longer timescale drought frequency, highlighting the fact that most climate models have difficulty in simulating extreme conditions. All three bias correction techniques analyzed in this study reduce biases in different timescale drought frequency. Correcting the biases in entire monthly precipitation time series and after separating monthly distribution showed no significant difference. The main function of using either the separate monthly series or the entire monthly series will similarly remove systematic bias in the mean and standard deviation. Similar performance of bias correction techniques in both cases gives general insight into the fact that there is no significant contribution from lack of fit of distribution because of few observations. However, robust conclusion requires further analysis.

Bias correction techniques such as EQM correct mean and distribution of the precipitation time series. However, they do not account for serial correlation. On the other hand, distribution- and persistence-based bias corrections such as NBC, using similar nesting methodology for different timescale (3-, 6-, and 12 months) and correcting only lag-1 autocorrelation as in this study, have limitations in widespread applications as discussed in a recent study by Nguyen et al. (2016). Bias correction techniques only correct the statistics of the precipitation time series not the point by point correction against the observations. In addition, bias correction techniques do not attribute biases to different underlying mechanisms of the climate system and their formulations in the climate models (e.g., Addor et al. 2016; Teutschbein and Seibert 2012). Extreme values might be modulated during bias corrections reducing the range of variability (Ehret et al. 2012) leading to different climate change signal. Moreover, random (unsystematic) errors in the climate model output might be attributed as systematic errors by the bias correction techniques (e.g., Maraun et al. 2010). A comprehensive review of critical issues of bias correction techniques has been documented in the literature (e.g., Ehret et al. 2012; Teutschbein and Seibert 2013) and should be considered before interpreting the results. Future work may focus on identifying the origins of these biases and take them into account. All bias correction techniques applied in this study assume that biases remain constant over time. The non-stationarity of biases in climate model simulated precipitation has already been noted by other studies (e.g., Chen et al. 2015), future work should emphasize on addressing the changing nature of such biases over time.

Even after bias correction, the two parameter gamma distribution cannot fit exactly to their empirical distribution. Hence some portion of the drought frequency (particularly severe drought frequency) might be the artifact of this lack of fit of distribution. In this study, we use three different combinations of two RCMs and two GCMs to give some general idea of effect in term of boundary conditions (as provided by RCMs) and climate model parameterizations (as provided by GCMs). While other models combinations from the NARCCAP can also be also used, future study should focus on effect of model parameterization (and boundary conditions) on simulating drought scenario and regional efficiency of bias correction technique.

5 Conclusions

In this study, we investigated climate models' ability to reproduce observed drought characteristics and examined future changes in drought frequency using the SPI as a drought monitoring index. We analyzed important features that should be preserved in analyzing drought characteristics based on bias correction on the precipitation results from RCMs. In addition, we examined the effects of temporal sequence of input precipitation time series in the bias correction. We then examined the future scenario drought severity and frequency compared with the historical scenario based on the precipitation output from several RCMs in the NARCCAP in representative locations in different climate regions across the USA. The main conclusions from this study can be summarized as follows:

1. Bias correction is important if the output from climate models (RCMs) is intended to analyze future drought frequency.
2. Three recently developed bias correction methods with different emphases all lead to similar performance. Preserving mean and standard deviation is essential for climate models in drought frequency analysis using SPI. Therefore, bias in mean and standard deviation of precipitation time series from climate models should be removed in drought

frequency analysis. While other higher order statistical moments can also be preserved, it is not essential in drought frequency analysis.
3. While seasonal considerations in drought analysis might be important, separating month of the year in precipitation time series for bias correction does not improve bias removal. Therefore, using the entire length of monthly time series of precipitation in bias correction is a convenient way in drought frequency analysis using SPI.
4. While bias correction is important in simulating and analyzing future drought scenarios, climate model data without bias corrections might be reasonable to be used directly if the goal is only to analyze future changes relative to the historic drought frequency, since inability of climate models to reproduce certain climate system dynamics may be similar in both historic and future scenario simulations and hence relative changes may also look similar even though climate models have biases in both scenarios.
5. Future drought changes have regional and time-scale dependence. Our analysis based on the results from the RCMs in the NARCCAP suggested that the percentage changes in drought frequency may vary from +51 to −57%. However, our analysis also pointed to the fact that bias could be larger than the predicted change.

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