Assessing the Spatiotemporal Uncertainties in Future Meteorological Droughts from CMIP5 Models, Emission Scenarios, and Bias Corrections

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ABSTRACT: Drought projections are accompanied with large uncertainties due to varying estimates of future warming scenarios from different modeling and forcing data. Using the standardized precipitation index (SPI), this study presents a global assessment of uncertainties in drought characteristics (severity $S$ and frequency $D_f$) projections based on the simulations of 28 general circulation models (GCMs) from phase 5 of the Coupled Model Intercomparison Project (CMIP5). A hierarchical framework incorporating a variance-based global sensitivity analysis was developed to quantify the uncertainties in drought characteristics projections at various spatial (global and regional) and temporal (decadal and 30-yr) scales due to 28 GCMs, three representative concentration pathway scenarios (RCP2.6, RCP4.5, RCP8.5), and two bias-correction (BC) methods. The results indicated that the largest uncertainty contribution in the globally projected $S$ and $D_f$ is from the GCM uncertainty (>60%), followed by BC (<35%) and RCP (<16%) uncertainty. Spatially, BC reduces the spreads among GCMs particularly in Northern Hemisphere (NH), leading to smaller GCM uncertainty in the NH than the Southern Hemisphere (SH). In contrast, the BC and RCP uncertainties are larger in the NH than the SH, and the BC uncertainty can be larger than GCM uncertainty for some regions (e.g., southwest Asia). At the decadal and 30-yr time scales, the contributions for three uncertainty sources show larger variability in $S$ than $D_f$ projections, especially in the SH. The GCM and BC uncertainties show overall decreasing trends with time, while the RCP uncertainty is expected to increase over time and even can be larger than BC uncertainty for some regions (e.g., northern Asia) by the end of this century.

KEYWORDS: Drought; Precipitation; Climate change; Climate prediction; Ensembles; General circulation models; Model comparison

1. Introduction

It is widely accepted that climate change is expected to influence the occurrence and magnitude of precipitation-associated extremes such as droughts (IPCC 2012; Orlowsky and Seneviratne 2013). Droughts are among the main natural hazards causing significant agricultural, economic, and environmental damages and losses (Wilhite 2000). During 1900–2004, 7% of the estimated U.S.$1.2 trillion in economic losses was due to drought, and more than half of all deaths associated with natural hazards are classified as drought-related (Below et al. 2007). More intense and longer droughts have been reported over larger areas since 1970s, particularly in semiarid and subhumid regions such as southern Europe and West Africa (Alley et al. 2007; IPCC 2012; Taylor et al. 2013). The global dry area has increased by ~1.74% decade$^{-1}$ from 1950 to 2008 (Dai 2011; Yu et al. 2014), with severe socioeconomic losses making droughts one of the most crucial targets for impact assessments of climate changes (Lehner et al. 2017). Quantitative assessment of the uncertainties in twenty-first-century drought projections is therefore of key importance for climate change adaptation and mitigation planning (Taylor et al. 2013).

One common way to investigate drought occurrence under climate change over the twenty-first century is the estimation of model-projected hydroclimate trends in drought variability (Cook et al. 2015). General circulation models (GCMs) simulating a long-term time series of hydrometeorological variables (e.g., temperature and precipitation) are the most common tools used for studying future climate extreme events (Sillmann et al. 2013a,b; Zhou et al. 2014; Xu et al. 2019a,b) and their impacts on global water disasters and water resources (Wetherald and Manabe 2002; Manabe et al. 2004; Wu et al. 2018).

Drought is usually monitored using the indices calculated from observed or GCM-simulated data (e.g., precipitation, temperature, and humidity) (Cook et al. 2015) or from the outputs (e.g., runoff) of global hydrological model simulations (Hagemann et al. 2013; Prudhomme et al. 2014). The influences of climate change on droughts have been investigated over many global regions by using a multitude of drought indices, such as the standardized precipitation index (SPI; Mishra and Singh 2009; Taylor et al. 2013; Duffy et al. 2015; Osuch et al. 2012; Taylor et al. 2013).

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the standardized precipitation evapotranspiration index (SPEI; Wu et al. 2016; Chen and Sun 2017; Gao et al. 2017; Spinoni et al. 2018), the Palmer drought severity index (PDSI; Wehner et al. 2011; Dai 2013; Taylor et al. 2013; Cook et al. 2015), the standardized runoff index (SRI; Taylor et al. 2013; Touma et al. 2015), the runoff deficit index (RDI; Prudhomme et al. 2014), and the soil moisture anomaly (SMA; Burke and Brown 2008; Taylor et al. 2013). Most of these studies have reported that the majority of drought-prone regions are likely to experience increasing drought risks under the persistent warming. However, considerable uncertainties exist in both observed and simulated drought data, particularly at the regional scale (Burke and Brown 2008; Dai 2011, 2013; Nasrollahi et al. 2015; Lehner et al. 2017).

It has been widely accepted that the deficiency in GCMs’ skills in simulating precipitation (Pr) and other atmospheric processes has led to substantial discrepancies among the simulated Pr trends from different models (Trenberth et al. 2014). No single model has demonstrated an overall superior skill relative to other models (Nasrollahi et al. 2015). Model projections, which by nature represent the multiple possible future outcomes, are highly uncertain particularly concerning the extent to which the drought occurrence and severity (e.g., SPI) are influenced by the spatial and temporal variability of Pr.

Recent studies have demonstrated that the projected future drought changes are highly associated with the choices of 1) GCMs, 2) greenhouse gas emissions scenarios (GGES), and 3) the bias-correction (BC) methods applied (Orlowsky and Seneviratne 2013; Taylor et al. 2013; Johnson and Sharma 2015; Zhao and Dai 2017; Lehner et al. 2017). For instance, Orlowsky and Seneviratne (2013) compared different uncertainty sources in meteorological and agricultural drought projections and indicated that the used GCMs are the dominant source of uncertainty for the longer-term projections (e.g., until the end of the twenty-first century). Ukkola et al. (2018) analyzed the agreement among different types of GCM-simulated drought and found that the spreads among GCMs are much larger than those among the ensemble members of individual models. The differences in simulated drought metrics are not only driven by the differences in simulated Pr that are closely linked to the component models. Model projections of drought characteristics are usually accompanied with large uncertainties due to varying emissions scenarios (Samaniego et al. 2018). In addition to that, various BC methods applied in the postprocessing of GCM-simulated data are also an important source of uncertainty, causing significant differences in drought assessments particularly when compared to results using the raw GCM data without corrections (Johnson and Sharma 2015).

Estimating the importance of different uncertainty sources in climate models is essential for climate studies. To the best of our knowledge, very few studies have considered the uncertainties of GGES, GCM, and BC simultaneously and estimated their relative contributions to the uncertainty in drought projections. Specifically, a systematic global assessment on the spatiotemporal distributions of uncertainties of GGES, GCM, and BC in drought projections remains largely unexplored.

Based on the SPI, one of the most commonly used meteorological drought indices (Mishra and Singh 2009; Duffy et al. 2015), here we present a systematic global assessment on the spatial distribution and temporal variability of the uncertainties in the projected drought characteristics (i.e., severity and frequency) by using 28 GCMs from phase 5 of the Coupled Model Intercomparison Project (CMIP5), three representative concentration pathway scenarios (RCP2.6, RCP4.5, and RCP8.5), and two BCs. A three-layer variance-based global sensitivity analysis framework was developed to quantify the uncertainties arising from the choice of GCMs, emission scenarios, and BCs.

The main objectives of this study are 1) to quantify the sensitivities of the trends and changes in projected drought characteristics to GCMs, RCP scenarios, and BC methods used, and 2) to estimate the individual contributions of GCM, RCP, and BC to the total uncertainties in projected drought characteristics at both spatial (global and regional) and temporal (decadal and 30-yr) scales. In the following, the detailed information on GCM data and other global gridded datasets used in this study are provided in section 2. The definitions and information of SPI, BC methods, trend analysis, and the framework of uncertainty estimation, are presented in section 3. Results and discussions are presented in sections 4 and 5, respectively, before the main conclusions drawn from this study are summarized in section 6.

2. Datasets

In this study, the 1971–2100 global gridded (1° × 1°) monthly Pr data were obtained from 28 CMIP5 GCMs (Table 1) provided by Canadian Climate Data and Scenarios (CCDS) at http://climate-scenarios.canada.ca/?page=gridded-data (Environment and Climate Change Canada 2020). Only one ensemble member (r1i1p1) under each RCP is used for each of the 28 GCMs in this dataset. This dataset has been used for evaluating the hydrologic impacts of future climate change over China (Wu et al. 2018).

Three time periods considered in this study include the baseline period (1971–2000) and two future periods [2041–70 and 2071–2100, hereafter referred to as near-future (NF) and far-future (FF) periods, respectively]. In addition, the 1971–2000 monthly Pr dataset from the Climatic Research Unit Time series (CRU TS) 3.22 (https://crudata.uea.ac.uk/cru/data/hrg/cru_ts_3.22/) was used for the bias correction of GCM Pr data in this study. The CRU TS dataset is gridded to 0.5° × 0.5° resolution, based on analysis of over 4000 individual weather station records (Harris et al. 2014). To ensure consistency in the spatial resolution among datasets used, the CRU TS Pr data (1971–2000) were resampled from the original 0.5° to 1° resolution using the bilinear interpolation without considering the effects of elevation (Tang et al. 2016).

3. Methodology

a. Bias correction of GCM outputs

As the biases in the climate models may lead to unreliable climate change assessments, the bias correction (BC) methods have been used in many model-based climate change impact
study (Johnson and Sharma 2015). BC has been an integral part of downscaling GCM simulation data (Christensen et al. 2008; Wood et al. 2002; Li et al. 2010; Maurer et al. 2010; Pierce et al. 2015) as a simple and effective method (Chen et al. 2013). In this study, two BC methods will be used to correct monthly Pr (Li et al. 2010) of which the parameters are estimated using the maximum likelihood method. To account for zero Pr, the following mixed-type gamma distribution is used (Li et al. 2010):

\[ G(x) = (1 - f)H(x) + fF(x), \]

where \( f \) is the percentage of months with rain; \( H(x) \) is the step function with the value either 0 (Pr = 0) or 1 (Pr > 0).

The second BC method used in this study is the “delta method” (hereafter BC2) in which the monthly GCM data are corrected by considering the changes in variance (Hawkins et al. 2013):

\[ \tilde{x}_{m,p} = x_{o,c} + \sigma_{m,c} (x_{m,p} - \bar{x}_{c}), \]

where the overbars denote the long-term mean, and \( \sigma_{m,c} \) and \( \sigma_{o,c} \) are the monthly standard deviations (STD) of the

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**Table 1. The CMIP5 GCMs used in this study. All the GCM simulations have been regridded onto a common 1° × 1° global grid by CCDS. The first ensemble member from each GCM’s simulations was used in this dataset.**

<table>
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<tr>
<th>Model</th>
<th>Institution and country</th>
<th>Native resolution</th>
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<td>BCC-CSM1.1</td>
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<td>128 × 64</td>
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<tr>
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<tr>
<td>BNU-ESM</td>
<td>College of Global Change and Earth System Science, Beijing Normal University, China</td>
<td>128 × 64</td>
</tr>
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<tr>
<td>CESM1-CAM5</td>
<td>Community Earth System Model Contributors, United States</td>
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</tr>
<tr>
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</tr>
<tr>
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<tr>
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</tr>
<tr>
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<tr>
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<td>GISS-E2-R</td>
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The standardized precipitation index (SPI) is a widely used meteorological drought index (McKee et al. 1993) for quantifying both wet and dry anomalies based on the degree to which the total Pr during a specified period deviates from the corresponding median. It is one of the major drought indices used by the World Meteorological Organization (WMO) and the National Drought Mitigation Center for the operational monitoring of long-term drought conditions. SPI offers several advantages over other commonly used drought indices, including the unambiguous theoretical development, robustness, temporal flexibility, and the simplicity since only Pr is required in calculation. The SPI has been widely used for the assessment of meteorological drought characteristics (including intensity, magnitude, duration, and spatial extent) under the past climates and future projections (e.g., Bordi et al. 2009; Taylor et al. 2013; Swain and Hayhoe 2015; Osuch et al. 2016). The SPI quantifies Pr deficit at multiple time scales (e.g., 1, 3, 6, 12, 24, and 48 months). At shorter time scales (e.g., 1 and 3 months) SPI reflects the characteristics of frequent changes between dry and wet conditions, whereas at longer time scales (e.g., 6 and 12 months) it reflects the slow-varying variability of dryness and wetness.

The first step in calculating SPI is the estimation of PDF of monthly Pr; then, the cumulative probability of Pr is computed and inversely transformed by the standard normal distribution with a zero mean and unit variance (McKee et al. 1993; Guttman 1999). In this study, the gamma distribution was used as the PDF of Pr following McKee et al. (1993) and Edwards and McKee (1997), with the parameters estimated by the maximum likelihood method. Considering that the calculation of SPI at longer time scales may be biased due to the limited data length used in fitting the distribution (Mishra and Singh 2010, Wu et al. 2005), the data in the baseline period 1971–2100 are used to fit the gamma distribution for calculating SPI over both the baseline (1971–2000) and future (2006–2100) periods.

The SPI is calculated globally only at the 6-month time scale (SPI6). SPI6 is chosen because at shorter time scales it may fail to detect longer periods of abnormally wet or dry conditions, while at longer time scales the dryness and wetness may show only little variability. As severe water supply and drought loss can be caused by any occurrence of SPI < 0 (Shiau 2006), a single meteorological drought event is defined here as a continuous period during which all the consecutive SPI6 are below 0. The severity (S) of each event is computed globally at each grid by using the runs theory (Yevjevich 1967) with the following definitions: S is the absolute value of the cumulative sum of SPI6 within the consecutive months for SPI6 < 0. The drought frequency (DF) is quantified by the number of drought events during a specified period.

Figures S1d–f compare the 1971–2000 simulated global-mean SPI6 based on the UC and two BC-corrected Pr data with that based on the observed CRU Pr data. As shown, all UC, BC1, and BC data can reproduce the ranges of SPI6 variability, but all of them tend to underestimate SPI6 in the 1970s and overestimate SPI6 during the 1991–94, suggesting that relative to UC, the two BC methods are unable to improve the temporal variability of SPI6.

d. Trend analysis

The Mann–Kendall (M–K) nonparametric trend test is a widely used method for detecting the significance of long-term trends (Yeh and Wu 2018; Zhang et al. 2020) due to the advantages of not assuming any distribution forms for the data and not being affected by interference from outliers (Mann 1945; Kendall 1975). More details about the M–K trend method can be found in Yu et al. (2014) and Wu and Huang (2015). In this study, the M–K trend test is applied to test the statistical significance of the trends in the long-term time series of the projected drought characteristics at each grid globally at the 0.05 significance level.

The variance-based global sensitivity analysis method has been widely used for quantification of uncertainty sources for various models (Chu-Agor et al. 2011; Saltelli 2000; Song et al. 2015; Vetter et al. 2017; Wagener and Pianosi 2019). This method has the advantage of directly quantifying the uncertainty of each source as achieved by filtering out the interaction terms between different sources and the capability of providing mathematically rigorous and accurate measurements for different uncertainty sources. In this study, an advanced hierarchical sensitivity analysis framework is developed based on the variance-based global sensitivity analysis method (Dai and Ye 2015; Dai et al. 2017a), which arranges the three identified uncertainty sources (GCM, RCP, and BC) based on the following deterministic relations among them: BCs depend on GCMs, and GCMs depend on RCP scenarios.

The core of the variance-based sensitivity analysis is the variance decomposition of model outputs (Dai et al. 2017a). This three-layer sensitivity analysis framework is applied to identify the relative contribution of GCM, RCP, and BC to the projected meteorological drought globally at each grid with the following steps (see appendix): First, decomposing the total
variance by three partial variances arising from GCM, BC, and RCP [Eqs. (A1)–(A4)]; second, calculating the partial variance contributed by these three uncertainty sources, respectively [Eqs. (A6)–(A8)]; and third, applying the individual partial variance divided by the total variance to compute the sensitivity indices of GCM, RCP, and BC [Eq. (A5)]. For better understanding the role of BC uncertainty in drought projections, UC is also included in this hierarchical sensitivity analysis framework so that the BC uncertainty denotes the differences between two BCs as well as between BCs and UC. Based on the sensitivity indices, the uncertainty contributions of GCM, RCP, and BC can be systematically evaluated at both spatial and temporal scales.

4. Results

a. Model agreement in projected trends in drought characteristics

The M-K trend test was used to test the significance of long-term (2006–2100) trends in $S$ simulated by 28 GCMs under three RCP scenarios at each grid globally. Figure 1 displays the global distribution of the number of GCMs projecting the significant increasing and decreasing (2006–2100) trends ($p < 0.05$) in $S$, considering different RCP scenarios for the UC, BC1, and BC2 cases. As shown, the global distributions of the numbers of GCMs projecting significant (increasing and decreasing) trends in $S$ for the UC and BC2 cases are similar over most global regions, with the spatial correlation coefficients ($r$) ranging from 0.7 (RCP2.6) to 0.96 (RCP8.5). In contrast, considerable discrepancy can be found between UC and BC1, particularly for the increasing trends under RCP2.6 ($r < 0.49$), indicating the relatively large uncertainty in selected BC methods to the projected trends of $S$.

Particularly under RCP8.5, there is high agreement among GCMs in the increasing drought risk in northern and southern South America, northern and southern Africa, southern Europe, southern North America, and some parts of western Asia, while there is high agreement among GCMs in the decreasing drought risk in northern North America and northern Asia. This finding is well supported by the median of 28-GCM projected trend magnitudes given in Fig. S2, showing that $S$ is generally projected to decrease in all high-latitude regions in NH under RCP8.5.

b. Model agreement in projected changes in drought characteristics

The global distributions of the number of GCMs projecting an increase in $S$ is plotted in Fig. 2, during the NF (2041–70) periods under all RCPs (relative to the baseline period). As shown, a relatively large discrepancy can be found between UC and two BCs in many global regions. The spatial $r$ between UC and BC1 is decreased from 0.24 (RCP8.5) to 0.12 (RCP2.6) during NF and from 0.84 (RCP8.5) to 0.18 (RCP2.6) during FF, while the spatial $r$ between UC and BC2 is decreased from 0.39 (RCP8.5) to 0.26 (RCP2.6) during NF and from 0.95 (RCP8.5) to 0.33 (RCP2.6) during FF. For some regions located in northern Asia, during the NF (2041–70) UC shows more than half of GCMs ($\geq 15$) projecting an increasing $S$, while BC1 and BC2 show only $\leq 10$ GCMs projecting an increasing $S$. During the FF (2071–2100) under RCP8.5, however, for some regions located in eastern Asia almost no GCMs project an increase in $S$ in the UC case, whereas more than half of GCMs project an increase in $S$ in the BC1 case. In addition, a larger discrepancy can be found between UC and BC1 than between UC and BC2 during both NF and FF periods under all RCPs (Fig. 2).

Figure 2 also shows that during the NF period less than half of GCMs project $S$ increases over most global regions under all RCPs. This is supported by Table S1 in the online supplemental material showing that the 28-GCM ensemble mean $S$ at the global scale is smaller under all RCPs during NF (2041–70) than during the baseline period (1971–2000). During the FF period (2071–2100), however, better agreement in the projected $S$ increase can be found among GCMs particularly under RCP8.5. A higher probability of increasing $S$ can be observed in northern and southern South America, northern and southern Africa, southern Europe, southern North America, and some parts of western Asia, while a lower probability can be found in all the high-latitude areas (mainly northern North America and northern Asia). This is consistent with the finding in Fig. S3, showing that the 28-GCM ensemble mean $S$ is larger in northern and southern South America, southern Europe, and northern Africa, but smaller in northern North America and northern Asia under RCP8.5 during the FF period relative to the baseline period.

Figure 3 plots the global distributions of the number of GCMs projecting an increase in $Df$ during both the NF and FF periods. Comparing with Fig. 2 (i.e., the numbers of GCMs projecting increasing $S$), there are more GCMs ($\geq 12$) projecting an increasing $Df$ than projecting an increasing $S$ for all three cases during NF for all RCPs and during FF except RCP8.5. For all cases plotted (three RCPs during NF and FF), UC and BC2 overall show more similar global patterns (with spatial $r$ of 0.6–0.65 and 0.63–0.85 in NF and FF, respectively) than that between UC and BC1 over some global regions such as the southwest and northern Asia (with a lower spatial $r$ of 0.36–0.42 and 0.38–0.7 in NF and FF, respectively).

Large spatial variability in the number of GCMs projecting an increasing $Df$ can be observed under all RCPs (Fig. 3). During NF, $\geq 12$ GCMs (43%–89%) project an increase in $Df$ over most global regions under all RCPs, especially in southern South America, northern Asia, and southern Africa, similar to that found under RCP2.6 and RCP4.5 during FF. However, for RCP8.5 during FF, very few ($\leq 4$) GCMs project an increasing $Df$ (drought risk) trend over most of the high-latitude regions located mainly in northern North America and northern Asia, which is opposite to that during NF. This is generally supported by Fig. S4 showing that the 28-GCM ensemble mean $Df$ is significantly smaller in northern North America and northern Asia under RCP8.5 during FF relative to that during the baseline period.

c. Uncertainty (spread) within models in projected changes in drought characteristics

The 28-GCM projected relative changes (%) in drought characteristics ($S$ and $Df$) during NF and FF relative to the baseline period are computed globally under all RCPs and for
all the UC, BC1 and BC2 cases. After that, the STDs of the projected relative changes in $S$ and $Df$ among 28 GCMs are computed and plotted in Figs. 4 and 5, respectively.

As shown in Fig. 4, the STDs of the projected changes in $S$ under all RCPs show similar global patterns during NF regardless of the BC methods used, but the STDs tend to be larger in northern Africa and northern South America during FF under RCP8.5. An apparent discrepancy in global patterns can be found between UC and BCs (BC1 and BC2) under all RCPs, but these differences tend to diminish under RCP8.5 during FF. The spatial $r$ between UC and BC1 is increased from 0.29–0.35 (NF) to 0.3–0.84 (FF), whereas that between UC and BC2 is increased from 0.52–0.56 (NF) to 0.54–0.9 (FF).

Fig. 1. The global distribution of the total number of GCMs projecting significant increasing and decreasing trends ($p < 0.05$) in $S$ during the period 2006–2100. The trend is tested by the Mann–Kendall test method at the 0.05 significance level.
The different BC methods used lead to an increase in the global range of the STD distribution in the projected changes in $S$ (Fig. 4). Compared with UC, both BC1 and BC2 have smaller STDs of the projected relative changes in $S$ in most of Asia and North America and southern Africa during NF (<25%; Fig. 4). In addition, BC2 has considerably larger STDs of the projected changes in $S$ in some regions located in northern Africa (>75%; Fig. 4).

For the STD of the projected change in Df among 28 GCMs shown in Fig. 5, the global-mean spatial $r$ between UC and BC1 is increased from 0.35–0.38 (NF) to 0.35–0.50 (FF), and between UC and BC2 is increased from 0.62–0.63 (NF) to 0.62–0.74 (FF). Compared to the projected changes in $S$ (Fig. 4), less inconsistency in the STD of projected Df changes can be found between NF and FF and among RCPs. However, considerable spatial variability across the global regions can still be

FIG. 2. The global distribution of the total number of GCMs projecting an increase in $S$ during the future periods (a) 2041–70 and (b) 2071–2100 relative to the baseline period (1971–2000).
observed, with larger STDs (20%–40%) observed in northern Africa, northern South America, and western Asia for most of cases plotted in Fig. 5.

The global distribution of the STD of the projected trends (2006–2100) in $S$ among 28 GCMs is plotted in Fig. S5. Similar to that found in Fig. 4, BC2 generally leads to larger STDs of the projected $S$ trends in northern Africa than that of UC. Spatially, larger STDs in the projected $S$ trends are found in some regions located in northern South America and northern Africa for both UC and two BCs particularly under RCP8.5.

**d. Sensitivity indices for the uncertainty contributions to the projected SPI6**

The sensitivity analysis is conducted in this subsection for the relative contributions of RCP, GCM, and BC to the total uncertainty in the projected SPI6 using the three-layer hierarchical
framework. The sensitivity indices for SPI6 are calculated at each grid globally using Eq. (A5).

Figure 6 plots the 2041–2100 monthly uncertainty contributions (i.e., the sensitivity indices) of different RCPs, GCMs, and BCs to the total uncertainties of the projected SPI6 for the global regions and six continents, respectively. Significant differences in the magnitudes of the relative uncertainty contributions of RCP, GCM, and BC can be observed among six continents. GCM is the most important source (>50%) of the total uncertainties in SPI6 projections for all continents, and this contribution is considerably larger in the SH (e.g., Africa, South America, and Oceania) than the NH (e.g., Asia, Europe, and North America). In contrast, the contributions from both BC and RCP are relatively limited in the SH.
(including South America, most of Africa, and Oceania) throughout the entire 2041–2100 period.

However, in the NH (Asia, Europe, and North America) the BC and RCP contributions are in general significant; in particular, the magnitude of BC contribution is close to that of GCM in Europe. Overall, GCM uncertainty has the largest contribution to the total uncertainties in SPI6 projections at the global scale throughout 2041–2100, but its dominance begins to decrease from 80% to 60% around 2070 toward the end of this century. BC is the second largest uncertainty source contributing to ~20% of total uncertainties in SPI6 projections. Relative to GCM and BC, RCP uncertainty is the least important uncertainty source (~20%) during most of the 2041–2100 period. However, the RCP uncertainty tends to decrease at first until the mid-twenty-first century and then increase gradually from 2070s onward until the end of the century when

![Figure 5](image-url)
it contributes up to 40% of total uncertainties, larger than the BC contribution.

**e. Sensitivity indices for the uncertainty contributions to the projected changes in drought characteristics**

The global distributions of uncertainty contributions from RCP, GCM, and BC (i.e., the sensitivity indices) to the projected changes in $S$ and $D_f$ (relative to the baseline period 1971–2000) are plotted in Figs. 7 and 8, respectively, at the decadal time scale (2041–50, 2051–60, ... 2091–2100) as well as two 30-yr periods (NF: 2041–70 and FF: 2071–2100). Comparisons between Figs. 7 and 8 show that the rankings of the relative uncertainty contributions of GCM, BC, and RCP are generally consistent in the projected $S$ and $D_f$ changes among the six decades analyzed. GCM uncertainty has the most dominant contribution (> 50%) to the total uncertainties for most global regions, with the contributions (mostly >80%) in the SH (particularly for southern Africa, South America, and Oceania) being larger than in the NH (~50%–60%). BC is the second largest uncertainty source for most global regions, with the contribution in the NH (~30%–68%) larger than that in the SH (mostly <30%). Compared with GCMs and BC, RCPs contribute the least to the total uncertainties over most global regions.

At regional scales in the NH (e.g., China), however, large variability in both GCM and BC uncertainty contributions can be observed at the decadal time scale, especially for the contribution to the total $S$ uncertainty (Fig. 7). The areas with BC uncertainty greater than GCM uncertainty in projected $S$ (Fig. 7) and $D_f$ (Fig. 8) changes during FF (2071–2100), mainly located in southwest Asia, account for 3.7% and 4.1% of the global land area, respectively. This suggests that the BC methods should be selected with caution over these regions. It is interesting to note that the uncertainty contribution from RCP to the uncertainty in $S$ and $D_f$ changes tends to increase over time during the FF period (2071–2100) in the high-latitude areas of NH, including northeast Asia and northern North America (up to 40%–63%; Figs. 7 and 8). The regions with the relative uncertainty contribution of RCP larger than that of BC accounts for 35.5% and 12.7% of the global land area in the projected $S$ and $D_f$ changes during FF, respectively, suggesting that RCPs should be considered as the critical uncertainty

Fig. 6. The 2041–2100 monthly time series of the uncertainty contributions (i.e., the sensitivity indices; %) from (a) BCs, (b) GCMs, and (c) RCPs to the total uncertainty of the projected SPI6.
FIG. 7. The global distributions of the uncertainty contributions (i.e., the sensitivity indices; %) from (a) BCs, (b) GCMs, and (c) RCPs to the projected changes in $S$ for each decade from 2041 to 2100 and two 30-yr periods (2041–2070 and 2071–2100) relative to the baseline period (1971–2000).
FIG. 8. As in Fig. 7, but for Df.
Figure 9 plots the relative uncertainty contributions of BC, GCMs, and RCPs to the projected changes in $S$ and $Df$ (relative to the baseline period 1971–2000) for the global regions and six continents for each decade from 2041 to 2100 and two 30-yr periods (2041–70, 2071–2100) relative to the baseline period 1971–2000.

5. Discussion

a. The hierarchical uncertainty analysis framework

Based on this uncertainty decomposition method, a multi-layer hierarchical uncertainty analysis framework is developed in this study for quantifying the contributions of three uncertainty sources (RCP, GCM, and BC) to the total uncertainties of GCM-projected drought characteristics. This framework explicitly quantifies the mutual dependence among GCM, RCP, and BC in sequence. The emission scenario uncertainty represented by RCP is model input and hence at the top level. GCM uncertainty caused by various conceptual or mathematical formulations of processes is driven by RCP scenarios, and hence is located at the middle level. The BC methods used as the post-processing to correct GCM outputs are situated at the lower level. Accordingly, the total uncertainty in projected drought characteristics is first decomposed into the contribution from RCP, followed by that from GCM and BC. Different from other commonly used sensitivity analysis methods such as the analysis of variance (ANOVA), the proposed framework directly quantifies the uncertainty of each source achieved by filtering out the interaction terms between different sources (see Fig. S6). The sensitivity indices (of the uncertainty sources) are estimated as

source in climate change impact assessment toward the end of the century in some high-latitude NH regions such as northeastern Asia and northern North America. However, the global areas with RCP contribution larger than GCM contribution only consist of a small fraction of global land area during FF (2.7% for $S$ and 0.02% for $Df$).
the individual partial variance divided by the total variance (Dai et al. 2017a).

The advantage is prominent since the interaction terms between various sources would become more complex as the number of uncertainty sources increases (e.g., see Fig. S6). More importantly, due to the advantageous capability of grouping uncertainty sources and considering their interdependence (Dai et al. 2017a,b), the proposed uncertainty analysis framework can theoretically be applied to \( n \) \((n \geq 2)\) kinds of uncertain sources involved from all the physical, chemical, and mathematical processes (including but not limited to emission scenarios, natural internal variability, climate models, postprocessing processes, and hydrological models, as well as model parameters) in the context of climate change impact studies.

### b. Uncertainties in drought characteristics projections

This study presents a global assessment of uncertainties in projected drought characteristics \((S\) and \(Df)\) from 28 GCMs, 3 RCP scenarios, and 2 BCs. The results indicate that GCM uncertainty has the largest contribution to the total uncertainty for most global regions, consistent with the findings in most recent studies (e.g., Giuntoli et al. 2015; Vetter et al. 2017; Xu et al. 2019b). The high GCM uncertainty results in large discrepancy in the number of GCMs projecting consistent trend direction and long-term mean changes in \(S\) and \(Df\) (Figs. 1–3). The relative contribution of GCM uncertainty is larger in the SH than the NH (Figs. 7 and 8), which generally agrees with the previous finding in the projected changes in runoff (Hagemann et al. 2013). The reason is mainly due to the smaller spreads in projected drought characteristics changes among GCMs in NH (e.g., Fig. 4) reduced by the application of BC methods (see Fig. S7).

At the decadal time scales, the GCM uncertainty decreases since 2070 until the end of the century (Fig. 6) and tends to be larger during NF than FF globally (Fig. 9), which is consistent with the previous model projections of extreme precipitation (Xu et al. 2019b), extreme hydrologic events (Giuntoli et al. 2018), and hydrologic regimes (Addor et al. 2014). The larger GCM uncertainty during NF than FF can be attributed to the more consistent drought projections among GCMs (particularly in northern North America and northern Asia under RCP 8.5) during FF than during NF (Figs. 2 and 3). In contrast, larger model spreads in projected drought changes (e.g., \(S\)) in the SH are found during FF than NF (Fig. 4), leading to a larger GCM uncertainty in Oceania and South America during FF (Fig. 9).

Note that GCM uncertainty considered here does not distinguish between the internal (natural) variability and model structure uncertainty. The \(Pr\) trend projected by each model is usually subject to the uncertainty due to internal variability (Deser et al. 2014), which can often be the dominant source of uncertainties in the near-term drought projections (Orlowsky and Seneviratne 2013). Further investigations are warranted by conducting multiple ensemble members analyses for various GCMs aiming at disentangling the relative contributions from the internal variability and model structure to the overall model projection uncertainties.

Both BC methods provide significant improvements of \(Pr\) variability for most global grids, but fail to improve SPI6 variability compared with UC (Fig. S1), suggesting that SPI-based drought metrics may mask some of the differences between two BCs. BC2 shows a more consistent global pattern of the projected drought trends with UC than BC1 (Fig. 1) since BC2 is a “delta method” that corrects model simulations by adding the changes in variance. Therefore, BC2 has the same STD as the observations and largely retains the original trend direction of model simulations (Hawkins et al. 2013). However, when the GCM-simulated \(Pr\) \((x_{\text{sim}})\) is considerably low in extremely dry months, BC2 may result in some negative \(Pr\) [see Eq. (3)]. In such circumstances, the simulated \(Pr\) cannot be corrected by BC2, hence resulting in smaller variability (smaller STD) of \(Pr\) relative to the observations (see Fig. S1).

Compared with UC, both BC methods (particularly BC2) tend to reduce the 28-GCM variability of \(S\) (Fig. S7), resulting in smaller variability of the projected \(S\) changes in many global regions (Fig. 4), particularly in the NH (e.g., northern North America and northern Asia). This suggests that the two BC methods can reduce GCM uncertainty in the projections of drought characteristics (e.g., \(S\)), a finding again consistent with previous studies (e.g., Johnson and Sharma 2015) indicating that the application of BC leads to improved consistency among GCMs and reduces the uncertainty in model structure. However, we also found an apparent discrepancy in the projections of drought variability between two BCs and between UC and BC especially in the NH (e.g., Fig. 4), which results in larger BC uncertainty in the NH than the SH (e.g., Fig. 7). Particularly over some global regions (e.g., southwest Asia), BC uncertainty can be larger than GCM uncertainty (Figs. 7 and 8), implying that the selection of appropriate BC methods is critical over these regions.

RCP uncertainty is generally the least important source of uncertainties relative to GCMs and BC in both SPI6 and drought characteristics projections. However, the RCP contribution to the uncertainty in global mean SPI6 projections tends to decrease first until the mid-twenty-first century before increasing from the 2070s onward until the end of the twenty-first century. This can be attributed to the smaller temporal variabilities of SPI6 under three RCPs in the 2060s than after the 2060s (Fig. S8). Overall, RCP uncertainty is found to grow over time (Figs. 7–9) with a larger uncertainty contribution during the FF than the NF period, consistent with the finding in the projections of the irrigation water demands (Wada et al. 2013), extreme precipitation events (Xu et al. 2019b), and hydrologic regimes (Addor et al. 2014; Giuntoli et al. 2018). For some regions located in Northeast Asia and northern North America, the uncertainty contribution by RCP can be \(>50\%

century under RCP8.5 (Fig. 1). In contrast, a high confidence of decreasing drought risk is identified in northern North America and northern Asia under RCP8.5 (Fig. 1). Particularly for some global regions (e.g., northern North America and northern Asia) under RCP8.5, the opposite signal in the projected Df changes between the early and late twenty-first century can be observed (Fig. 3), suggesting the nonlinear response of projected Df changes to anthropogenic forcing.

Our results at the regional scale, however, are somewhat different from several drought assessment studies using different drought indices such as PDSI (Dai 2013; Zhao and Dai 2017) and the SMA (Sheffield and Wood 2008; Burke 2011). Most of these studies indicated a generally continuing increase in global drought occurrence over the twenty-first century owing to the increased potential evaporation due to climate warming. Note that most of these studies were based on the offline drought metrics computed from model output data rather than using the direct model projections, since climate models do not directly simulate the obvious increase in the aridity with the increasing CO2 concentration (e.g., Roderick et al. 2015; Greve et al. 2017; Yang et al. 2019; Milly and Dunne 2016; Swann et al. 2016; Berg et al. 2017).

Note that the SPI used in this study only represents meteorological drought occurrence and provides limited information on the potential impacts of droughts on agriculture, ecosystems, and societies. Large disagreement in model projections for different types of droughts have been widely reported (Burke and Brown 2008; Touma et al. 2015; Rhee and Cho 2016), implying that the impacts of climate change on future drought occurrence are highly uncertain if only a single drought index is used. Incorporation of multiple drought metrics can effectively enhance the reliability of drought projections particularly at the regional scale.

Also note that the definition of a drought event (SPI < 0) in this study is looser than that (e.g., SPI < −0.5 or −1) in some previous studies (e.g., Zhai et al. 2010). For example, the percentage of drought length with SPI < 0 (i.e., 50% of time series) is ~20% and 40% larger than that with SPI < −0.5 and SPI < −1, respectively, for most global grids (Fig. S9). This suggests that the definition of drought may be a potential source of uncertainty in explaining model differences, which calls out the need for more research into the sensitivity of drought projections to the thresholds of drought definition.

The downscaling (including statistical and dynamical methods) of large-scale GCM output to a finer spatial resolution is needed in climate change assessment studies, due to the gap between the resolution of climate models and regional- and local-scale processes (Fowler et al. 2007). The 28-GCM dataset used was spatially downscaled onto the 1° × 1° grid resolution by the CCDS. In this study, the BC methods are implemented on a grid of the same spatial resolution (1° × 1°) and hence the effects of spatial downscaling (from coarse to high resolution) on the uncertainty contribution of GCM are not considered. However, there is a large uncertainty envelope associated with the choice of a downscaling method in climate change impact studies (Chen et al. 2011, 2012; Sunyer et al. 2012), suggesting that climate change impact studies based on only one downscaling method should be interpreted with caution. Comprehensive investigations into the sensitivities of drought projections to different spatial downscaling methods are indispensable in future research.

6. Conclusions

Using the standardized precipitation index (SPI), here we investigate the spatial patterns and temporal variability of different sources of uncertainty in global drought projections based on 28 CMIP5 GCMs, three climate change scenarios (RCP2.6, RCP4.5, and RCP8.5), and two BC methods. The uncertainties in the model projections of drought characteristics (S and Df) from GCMs, RCPs, and BCs are estimated separately using the three-layer hierarchical sensitivity analysis. Systematic comparisons among model projections for different drought characteristics are made in global regions at both spatial and temporal scales.

The results indicate that the overall uncertainty in drought characteristics projection is dominated by GCM for most global regions. Globally, GCM has relatively larger uncertainty in SH than NH, whereas BC and RCP both have relatively larger uncertainties in NH than SH (Figs. 7 and 8). BC methods are the second largest uncertainty source for GCM drought projections, and for some global regions (e.g., southwest Asia) BC uncertainty can be greater than GCM uncertainty and even can alter the trend direction of the projected drought characteristics. At decadal time scales, the uncertainties of GCM and BC are projected to decrease over time toward the end of twenty-first century (Fig. 9). For some regions in the NH (e.g., China), significant interdecadal variability in the relative uncertainty contributions of GCM and BC can be found (Fig. 8). Compared with GCM and BC, RCP is the least important uncertainty source (<20% contribution) for most cases considered. However, the uncertainty of RCP is expected to increase over time and can even be larger than that of BC for some regions (e.g., northern Asia) by the end of this century (Figs. 7 and 8). Overall, the results of this study highlight the large spatial and temporal variations of three main uncertainty sources (GCM, RCP, and BC). Further advanced investigations in the uncertainty analysis of hydrometeorological predictions are necessary within the context of climate change impact studies.

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APPENDIX

The Calculation of Sensitivity Indices for the Three-Layer Sensitivity Analysis Framework

For a model with the form of $\Delta = f(\theta) = f(\theta_1, \ldots, \theta_k)$, where $\Delta$ is the model output and $\theta = [\theta_1, \ldots, \theta_k]$ is the set of uncertain model inputs, the total variance ($V$) can be decomposed as (Xu et al. 2019b) follows:

$$V(\Delta) = E_{\theta} [E_{\theta_j} (\Delta | \theta_j)] + E_{\theta_j} [E_{\theta_j} (\Delta | \theta_j)]. \quad (A1)$$

where $E$ represents mathematical expectation, and $V$ represents mathematical variance. In Eq. (A1), the first term on the right side is the partial variance contributed by the $j$th uncertain input ($\theta_j$), while the second term is the partial variance contributed by all other uncertain inputs except $\theta_j$. Based on the Eq. (A1), the total variance can be decomposed as

$$V(\Delta) = V_R [E_{-\theta_R} (\Delta | R)] + E_R [V_{-\theta_R} (\Delta | R)]$$
$$= V_R [E_{\theta_R} (\Delta | R)] + E_R [V_{\theta_R} (\Delta | R)]. \quad (A2)$$

where $R$ is the set of multiple RCPs, $G$ is the set of multiple GCMs, $B$ is the set of multiple BC methods, and $\sim R$ represents all uncertain factors excluding $R$, which in this study are $G$ and $B$. The subscript $GCB\!\!R$ represents the contributions of different GCMs and BC methods under a certain RCP.

The two terms in Eq. (A2) refer to the variances due to RCP uncertainty and other uncertainties, respectively. The partial variance caused by other uncertainty sources, $V_{GCB\!\!R}(\Delta | R)$, can be further decomposed based on multiple GCMs as the following:

$$V_{GCB\!\!R}(\Delta | R) = V_{\theta_R}[E_{-\theta_G} (\Delta | G, R)]$$
$$+ E_{\theta_G}[V_{-\theta_G} (\Delta | G, R)]$$
$$= V_{\theta_R}[E_{\theta_G} (\Delta | G, R)]$$
$$+ E_{\theta_G}[V_{\theta_G} (\Delta | G, R)]. \quad (A3)$$

where the subscript $BC|GR$ represents the change of BC methods under certain fixed GCMs and RCPs, suggesting that the BC methods are conditioned on GCMs and RCPs in the hierarchical framework.

Substituting Eq. (A3) into Eq. (A2), the total variance can be decomposed as

$$V(\Delta) = V_R [E_{GCB\!\!R}(\Delta | R)] + E_R [V_{GCB\!\!R}(\Delta | G, R)]$$
$$+ E_{\theta_R}[E_{G} (\Delta | G, R)]$$
$$= V_R [E_{GCB\!\!R}(\Delta | G, R)]$$
$$+ E_R [V_{GCB\!\!R}(\Delta | G, R)]$$
$$+ E_{\theta_R}[E_{G} (\Delta | G, R)]$$
$$= V(R) + V(G) + V(B). \quad (A4)$$

Applying the individual partial variance divided by the total variance, the sensitivity of RCPs ($S_R$), GCMs ($S_G$), and BC methods ($S_B$) can be expressed as

$$S_R = \frac{V_R [E_{GCB\!\!R}(\Delta | G, R)]}{V(\Delta)} = \frac{V(R)}{V(\Delta)}$$
$$S_G = \frac{E_R [V_{GCB\!\!R}(\Delta | G, R)]}{V(\Delta)} = \frac{V(G)}{V(\Delta)}$$
$$S_B = \frac{E_R [V_{GCB\!\!R}(\Delta | G, R)]}{V(\Delta)} = \frac{V(B)}{V(\Delta)}. \quad (A5)$$

Assuming $k$ alternative RCPs, $j$ different GCMs, and $n$ plausible BC methods, the uncertainty of BC methods can be estimated as

$$V(BC) = E_R [V_{GCB\!\!R}(\Delta | G, R)]$$
$$= \sum_j \sum_i \left\{ \frac{1}{n} \sum_{k=1}^{n} \Delta R_k \right\} \left( P(GC|R_k)P(R_k) \right) \left( P(GC|R_k)P(R_k) \right) \cdot \quad (A6)$$

where $P(GC|R_k)$ is the weight of GC under RCP $k$ satisfying $\sum_{i=1}^{n} P(GC|R_k) = 1$, and $P(R_k)$ is the weight of RCP $k$ satisfying $\sum_{i=1}^{n} P(R_k) = 1$. In this study, the weights of RCPs, GCMs, and BC are considered as identical when calculating the expectation. Similarly, the partial variances of GCM and RCP can be calculated as

$$V(G) = E_R [V_{GCB\!\!R}(\Delta | G, R)]$$
$$= E_R [V_{GCB\!\!R}(\Delta | G, R)]^2$$
$$- [E_{GCB\!\!R}(\Delta | G, R)]^2$$
$$= \sum_i P(R_k) \left\{ \sum_{j=1}^{n} \Delta R_k \left( P(GC|R_k) \right) \right\}^2 \cdot \quad (A7)$$

$$V(R) = E_R [V_{GCB\!\!R}(\Delta | G, R)]$$
$$= E_R [V_{GCB\!\!R}(\Delta | G, R)]^2$$
$$- [E_{GCB\!\!R}(\Delta | G, R)]^2$$
$$= \sum_i P(R_k) \left\{ \sum_{j=1}^{n} \Delta R_k \left( P(GC|R_k) \right) \right\}^2 \cdot \quad (A8)$$

Based on the above Eqs. (A6)–(A8), the sensitivity indices defined in Eq. (A5) above can be evaluated.


