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Why Do Different Drought Indices Show Distinct Future Drought Risk Outcomes in the U.S. Great Plains?

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ABSTRACT

Vigorous discussions and disagreements about the future changes in drought intensity in the U.S. Great Plains have been taking place recently within the literature. These discussions have involved widely varying estimates based on drought indices and model-based projections of the future. To investigate and understand the causes for such a disparity between these previous estimates, the authors analyzed the soil moisture at the near-surface soil layer and the entire soil column, as well as the Palmer drought severity index, the Palmer Z index, and the standardized precipitation and evaporation index using the output from the Community Climate System Model, version 4 (CCSM4), and 25 state-of-the-art climate models. These drought indices were computed using potential evapotranspiration estimated by the physically based Penman–Monteith method (PE_pm) and the empirically based Thornthwaite method (PE_th). The results showed that the short-term drought indices are similar to modeled surface soil moisture and show a small but consistent drying trend in the future. The long-term drought indices and the total column soil moisture, however, are consistent in projecting more intense future drought. When normalized, the drought indices with PE_th all show unprecedented future drying, while the drought indices with PE_pm show comparable dryness with the modeled soil moisture. Additionally, the drought indices with PE_pm are closely related to soil moisture during both the twentieth and twenty-first centuries. Overall, the drought indices with PE_pm, as well as the modeled total column soil moisture, suggest a widespread and very significant drying in the Great Plains toward the end of the century. The results suggest that the sharp contrasts about future drought risk in the Great Plains discussed in previous studies are caused by 1) comparing the projected changes in short-term droughts with that of the long-term droughts and/or 2) computing the atmospheric evaporative demand using an empirically based method (e.g., PE_th). The analysis here may be applied for drought projections in other regions across the globe.

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1. Introduction

Drought is a ubiquitous feature of the U.S. Great Plains (30°–50°N, 105°–95°W) climate. This region was plagued by decadal droughts in the 1930s and 1950s and short droughts in 1988 and 2012. These droughts tremendously affected the regional economy and ecosystems (NCEI 2014). Given the importance of agriculture within the Great Plains to the global economy, and the more local impacts on the livelihoods and environments of the region, it is important to obtain reliable projections of the changes in future drought in the Great Plains.

There are considerable uncertainties and vigorous discussions, however, involving recent and projected future drought intensities in the Great Plains as well as other global land areas. These different views about future drought characteristics in the Great Plains contrast sharply because different drought indices were used in the evaluations. The Palmer drought severity index (PDSI; Palmer 1965) suggests more intense drought in the future across the Great Plains (Dai 2011a, 2013; Cook et al. 2014). Soil moisture projection, on the other hand, suggests weak drying over the Great Plains (Hoerling et al. 2012; Winter and Eltahir 2012). Hoerling et al. (2012) compared the projected changes in drought in the Great Plains as inferred from the PDSI and soil moisture within the top 10 cm of the soil column (SM10). They found that the PDSI is an excellent indicator for SM10 in the Great Plains in the twentieth century, but the PDSI severely overestimated the future surface water imbalances and implied agricultural stresses. They further argued that the PDSI is unrealistically sensitive to the projected warming and is probably unsuitable for future drought projections. In the standard PDSI calculation, the potential evapotranspiration (PE) is estimated using the empirically based Thornthwaite method (PE_th; Thornthwaite 1948). The variations of PE_th in a given region depend only on temperature. It was found that PE_th is very sensitive to temperature changes, causing it to depict more severe droughts (Sheffield et al. 2012; Dai 2011b). Another commonly used PE method is the Penman–Monteith method (PE_pm; Allen et al. 1998), which is based on the combination of radiative and aerodynamic components at the surface. This physically based method accounts for the impacts of temperature, solar radiation, wind speed, and relative humidity on PE (Allen et al. 1998; SchefF and Frierson 2014). Compared to PDSI calculated based on PE_th, the PDSI calculated based on PE_pm generally depicts less severe drought conditions in recent decades (Sheffield et al. 2012) and in the future (Dai 2013; Cook et al. 2014). Therefore, using different PE methods may lead to considerable differences in PDSI values.

Because different drought indices contrast sharply about the future drought risk, it is important to compare these indices to understand why their results are different. Trenberth et al. (2014) provided a comprehensive synopsis of the global drought discrepancies during the instrumental period. They suggested that the discrepancies lie in the formulation of the PDSI and the meteorological datasets used to determine the PE. The uncertainties in the precipitation as well as the natural variability, especially the effect of El Niño–Southern Oscillation and the Pacific decadal oscillation, also appreciably contribute to the drought discrepancies. However, Trenberth et al. (2014) focused merely on the instrumental period; it is thus necessary to evaluate the drought discrepancies in the future.

It is commonly accepted that drought is a multiscale phenomenon (Vicente-Serrano et al. 2010). The time scale over which water deficits accumulate is important (McKee et al. 1993; Vicente-Serrano et al. 2013), and it functionally separates meteorological, agricultural, hydrological, and socioeconomic drought as suggested by Heim (2002). The PDSI is an indicator of longer-term (usually ≥9 months) drought (Guttman 1998; Vicente-Serrano et al. 2010). The shallow layer soil moisture (e.g., SM10), on the other hand, can change instantly following relatively small precipitation events. Therefore, SM10 is an indicator of short-term drought because it is sensitive to unusual wet (or dry) months even in an extended dry (or wet) period. Additionally, the multiscale standardized precipitation evapotranspiration index (SPEI; Vicente-Serrano et al. 2010) has also been used for future drought projections in recent studies (e.g., Barrera-Escoda et al. 2014; Hernandez and Uddameri 2014; Cook et al. 2014; Jeong et al. 2014; Touma et al. 2015). The SPEI works as pure climate water balance and responds equally to changes in precipitation and atmospheric evaporative demand (Vicente-Serrano et al. 2010). As the SPEI is relatively new, there is an opportunity to investigate how the SPEI performs in quantifying future droughts.

It was found that different drought indices show varying sensitivity to precipitation and temperature (used to calculate PE) variations. Vicente-Serrano et al. (2015) extensively analyzed the sensitivity of PDSI, SPEI, and another two drought indices to changes in precipitation and PE. They found that the PDSI is more sensitive to the variations of precipitation than to PE, while the SPEI is equally sensitive to the variations of precipitation and PE. These results suggest that some drought indices may be more sensitive to climate changes, which in turn would lead to large differences in future drought conditions. The objective of this study is to compare a suite of drought
indices to evaluate projections of future drought intensity over the Great Plains and to figure out why they show different future drought risk outcomes. Ultimately, this may lead to better understanding of the source of uncertainties in future droughts and better water management and drought risk management in the region.

2. Data and methods

We used the output from the Community Climate System Model, version 4 (CCSM4; Gent et al. 2011), with specified historical anthropogenic and natural external forcings during 1850–2005 (historical run) and with twenty-first-century changes in greenhouse gases and anthropogenic aerosols, following the representative concentration pathway 8.5 (RCP8.5) for 2006–2100. Hoerling et al. (2012) also analyzed the CCSM4 simulations and concluded that the PDSI is not suitable for future drought projections. Therefore, using the CCSM4 output ensures a fair comparison of our results with that of Hoerling et al. (2012). Additionally, the Community Land Model version 4 (CLM4) used in CCSM4 is significantly improved in simulating the soil water storage, evapotranspiration, surface albedo, and permafrost and thus represents a significant advance over prior versions (Lawrence et al. 2011, 2012). Over the U.S. Great Plains region, the land model incorporates 10 soil layers to ~3 m. We analyzed monthly output from an ensemble of six CCSM4 simulations, and the simulated monthly precipitation, temperature, solar radiation, relative humidity, and wind speed as well as the monthly soil moisture were used. This study analyzed the soil moisture over the top-10-cm layer (SM10) and the total soil column (SMTC). Unlike SM10, the SMTC records more lower-frequency variations in soil water balances and can be considered as a long-term drought indicator. Oglesby et al. (2002) also found that the soil moisture in deeper soil layers is more important in explaining the interannual to decadal droughts evident in the historic and recent prehistoric records but less important on monthly to seasonal time scales.

In addition to CCSM4, we also analyzed the simulations from 25 global climate models (Table 1) in phase 5 of the Coupled Model Intercomparison Project (CMIP5) database (Taylor et al. 2012). For models with multiple ensemble runs, the first ensemble run was used. We focused on the historical run during 1850–2005 and the RCP8.5 scenario during 2006–2100. The surface soil moisture from these CMIP5 models was integrated from the surface to about 30 cm (SM30), while the total column soil moisture was integrated from the surface to about 2–3 m (SM2m; Cook et al. 2015). Compared to the SM10 in CCSM4, the SM30 in the CMIP5 records more lower-frequency variations in soil moisture. Because the

| Model Name | Origin |
|------------|--------|
| ACCESS1.0  | Commonwealth Scientific and Industrial Research, Australia |
| ACCESS1.3  | Commonwealth Scientific and Industrial Research, Australia |
| BCC_CSM1.1 | Beijing Climate Center, China |
| CanESM2    | Canadian Centre for Climate, Canada |
| CESM1(BGC) | National Center for Atmospheric Research |
| CNRM-CM5   | Centre National de Recherches Météorologiques, France |
| CSIRO Mk3.6.0 | Commonwealth Scientific and Industrial Research, Australia |
| FGOALS-g2  | Institute of Atmospheric Physics, Chinese Academy of Sciences, China |
| GFDL CM3   | Geophysical Fluid Dynamics Laboratory |
| GFDL-ESM2G | Geophysical Fluid Dynamics Laboratory |
| GFDL-ESM2M | Geophysical Fluid Dynamics Laboratory |
| GISS-E2-H  | NASA Goddard Institute for Space Studies |
| GISS-E2-R  | NASA Goddard Institute for Space Studies |
| HadGEM2-CC | Met Office Hadley Centre, United Kingdom |
| HadGEM2-ES | Met Office Hadley Centre, United Kingdom |
| INM-CM4    | Institute for Numerical Mathematics, Russia |
| IPSL-CM5A-LR | L’Institut Pierre-Simon Laplace, France |
| IPSL-CM5A-MR | L’Institut Pierre-Simon Laplace, France |
| IPSL-CM5B-LR | L’Institut Pierre-Simon Laplace, France |
| MIROC5     | Atmosphere and Ocean Research Institute, Japan |
| MIROC-ESM  | Japan Agency for Marine-Earth Science and Technology, Japan |
| MIROC-ESM-CHEM | Japan Agency for Marine-Earth Science and Technology, Japan |
| MRI-CGCM3  | Meteorological Research Institute, Japan |
| NorESM1-M  | Norwegian Climate Centre, Norway |
| NorESM1-ME | Norwegian Climate Centre, Norway |
land models used in the CMIP5 models differed considerably in soil physics, surface vegetation, and number of soil layers (Cook et al. 2015), it is difficult to directly compare the variations of SM30 or SM2m among the CMIP5 models. Therefore, this study mainly focused on the simulations of CCSM4, while the CMIP5 simulations were used for verification and validation. Besides the CCSM4 and the CMIP5 simulations, the global precipitation, temperature, and PE_pm data from the Climatic Research Unit (CRU) TS3.23 datasets (Harris et al. 2014) are also used. These datasets cover the global land areas at 0.5° resolution in latitude and longitude. Because the CRU did not provide PE_th, we calculated it using the TS3.23 temperature dataset. The CRU datasets cover the period 1901–2014 and are based on observations from thousands of weather stations. Therefore, they can be used to evaluate the CCSM4 and the CMIP5 models.

The PDSI first computes the monthly soil moisture departure based on the water supply and demand at the surface level as well as the local climate characteristics (Palmer 1965; Wells et al. 2004). These monthly values are called the Palmer Z index (ZIND). The PDSI values are then estimates of the effect of accumulated water deficit over an extended time period. The ZIND is not affected by water deficit in previous months, and its values can vary dramatically from month to month. Therefore, the ZIND can be used to quantify short-term drought (e.g., Wells et al. 2004). Both PE_th and PE_pm are calculated and then used to calculate the PDSI and ZIND. Accordingly, the PDSI and ZIND based on PE_th and PE_pm are termed as PDSI_th, PDSI_pm, ZIND_th, and ZIND_pm, respectively. This study used the self-calibrated method developed by Wells et al. (2004) and a snow-melting module (Van der Schrier et al. 2007) to calculate the PDSI and ZIND. The parameters for calculating PDSI and ZIND values are determined from the monthly model output during 1901–2000 for each of the six ensemble runs, and then the self-calibrated PDSI and ZIND values are calculated during the entire 1850–2100 for each model run using the corresponding parameters. Droughts are defined as PDSI < −1.00, which are further divided into mild drought (−1.99 < PDSI < −1.00), moderate drought (−2.99 < PDSI < −2.00), severe drought (−3.99 < PDSI < −3.00), and extreme drought (PDSI < −4.00; Palmer 1965). The ZIND classifies the droughts using the same set of criteria.

The multiscalar SPEI (Vicente-Serrano et al. 2010; Beguería et al. 2014) was also used to quantify the future drought in the Great Plains. Typically, the SPEI is computed based on 1, 3, 6, or 12 months of accumulation of water surpluses and deficits (precipitation minus PE), and then those quantities are fit using statistical probability distributions, termed as 1-, 3-, 6-, or 12-month SPEI, respectively. Since the SPEI represents departures in climatological balance between water availability and atmospheric water demand, it is slightly different from the PDSI (Vicente-Serrano et al. 2015). This study only computed the 1- and 12-month SPEI, which can be used to quantify the short-term and long-term drought, respectively. Like the PDSI, we calculated the SPEI using the PE computed by both PE_th and PE_pm methods, termed as SPEI_th and SPEI_pm, respectively. The SPEI was classified as mildly dry (−0.99 < SPEI < 0.00), moderate drought (−1.49 < SPEI < −1.00), severe drought (−1.99 < SPEI < −1.50), and extreme drought (SPEI < −2.0), respectively (Vicente-Serrano et al. 2010). For better comparison, the SPEI is also calibrated using the same standardization interval as PDSI, 1901–2000. For soil moisture, the monthly SM10 and SMTC in CCSM4 and the SM30 and SM2m in CMIP5 models are also normalized based on mean and standard deviation during 1901–2000.

The drought indices we evaluated are summarized in Table 2. It is worth noting that these drought indices were usually used to quantify different type of droughts. The soil moisture is usually used to quantify

| PE and drought indices | Climate variables | Description |
|------------------------|-------------------|-------------|
| PE_pm                  | T_air, RH, R, WS  | PE calculated by Penman–Monteith method |
| PE_th                  | T_air, latitude   | PE calculated by Thornthwaite method |
| PDSI_pm                | P, PE_pm         | Self-calibrated PDSI based on PE_pm |
| PDSI_th                | P, PE_th         | Self-calibrated PDSI based on PE_th |
| ZIND_pm                | P, PE_pm         | Self-calibrated Palmer Z index based on PE_pm |
| ZIND_th                | P, PE_th         | Self-calibrated Palmer Z index based on PE_th |
| SPEI_pm_01             | P, PE_pm         | 1-month SPEI based on PE_pm |
| SPEI_th_01             | P, PE_th         | 1-month SPEI based on PE_th |
| SPEI_pm_12             | P, PE_pm         | 12-month SPEI based on PE_pm |
| SPEI_th_12             | P, PE_th         | 12-month SPEI based on PE_th |

Table 2. Description of the drought indices and the model variables used in their calculation. The model variables used are surface air temperature T_air, relative humidity RH, solar radiation R, surface wind speed WS, and precipitation P.
the agricultural drought (Dai 2011a), while the SPEI are used to quantify the meteorological drought (Vicente-Serrano et al. 2010, 2015; Beguería et al. 2014). The PDSI is also a meteorological drought index (Palmer 1965). However, it is most effective in measuring the drought impacts that are sensitive to soil moisture conditions, such as in agriculture production. Therefore, the drought indices evaluated in this study do not necessarily represent the same type of drought. The objective of this study is not to compare different types of droughts (e.g., agricultural vs meteorological droughts). Rather, we focus on the short- and long-term droughts and their future variations.

3. Results

To evaluate the performance of climate models in simulating the climate variations in the Great Plains, we compare the modeled annual precipitation, temperature, PE_pm, and PE_th average over the Great Plains with the CRU datasets. Though the relative humidity, solar radiation, and wind speed are also variables necessary to quantify the PE_pm and the drought severity based on it, we did not evaluate these quantities because there are large uncertainties in the observations (Trenberth et al. 2014; Beguería et al. 2014). As shown in Fig. 1, the CCSM4 as well as the CMIP5 models simulated the
mean and temporal variability (standard deviation) of the annual temperature and \( PE_{th} \) reasonably well, except the CCSM4 overestimates the temporal variability of temperature. Additionally, the models simulated similar temporal variability in the annual precipitation and \( PE_{pm} \), but the models overestimated (underestimated) the long-term climatology of the precipitation (\( PE_{pm} \)). Similar results can be found when comparing the modeled warm-season precipitation, temperature, \( PE_{pm} \), and \( PE_{th} \) in the Great Plains with the observations (figure omitted). These differences may be caused by the model bias and, to a lesser degree, the uncertainties in the observations in precipitation, radiation, relative humidity, and wind speed (e.g., Trenberth et al. 2014; Beguería et al. 2014). These differences may affect the future drought variability as different drought indices show various responses to precipitation and PE (Vicente-Serrano et al. 2015). However, it is difficult to quantify the contribution of these relatively small differences between the models and observations to the future drought variability. Since we are comparing the modeled drought variability in the future with the modeled drought variability during the twentieth century, the impact of model uncertainty could be small. Therefore, it is reasonable, though certainly not perfect, to use CCSM4 and CMIP5 models to quantify the future drought variability.

Figure 2 shows the temporal variations of SMTC, \( PDSI_{pm} \), \( ZIND_{pm} \), and 1-month and 12-month \( SPEI_{pm} \) (termed as \( SPEI_{pm\_01} \) and \( SPEI_{pm\_12} \), respectively) averaged over the Great Plains for each of the six CCSM4 simulations (gray curves) and their ensemble average (black curves) for the period of 1850–2100. For comparison, the ensemble average of precipitation, \( SM10 \), \( PDSI_{th} \), \( ZIND_{th} \), and 1-month and 12-month \( SPEI_{th} \) (termed as \( SPEI_{th\_01} \) and \( SPEI_{th\_12} \)) are also shown in Fig. 2. All drought indices suggested a decadal-long drought event in the late 1860s in one of the model simulations. This is also the worst event from all of the ensemble members. The ensemble runs were started from random initial conditions in 1850 when there were few observations with common external forcing data. Therefore, individual ensemble runs contain internal variability of the climate system, while the ensemble mean of these simulations should be interpreted as an estimate of climate response to natural and anthropogenic forcing (Fu et al. 2016). Additionally, since the 1860s droughts in one of the model simulations occurred during a period of fairly limited influence of climate forcings (e.g., 1850–1950), Hoerling et al. (2012) considered it as a randomly occurring severe drought due to internal model variability. Because this modeled drought event has many of the meteorological characteristics of severe drought over the Great Plains during the 1930s (Hoerling et al. 2012; see their Fig. 2), we consider this event as the benchmark to compare the future drought conditions. The magnitude of this event is shown as the dashed line in Fig. 2.

The precipitation fluctuated around the normal during the entire analysis period, with slightly increasing precipitation after the 2050s (Fig. 2a). Unlike precipitation, all drought indices show steadily decreasing values (more droughts) beginning in the late twentieth century, as a result of PE increases. The indices based
on PE_pm (PDSI_pm, ZIND_pm, SPEI_pm_01, and SPEI_pm_12) project gradually increasing dryness in the future. By the end of this century, the mean intensity of droughts is comparable to the worst severe drought during 1850–1950 (Fig. 2). The drought indices based on PE_th (PDSI_th, ZIND_th, SPEI_th_01, and SPEI_th_12) all show more intense drying in the future compared to that based on PE_pm. By the end of this century, the drought indices based on PE_th show unprecedented dry conditions compared to all historical runs during 1850–2005.

There are great differences between the magnitudes of projected short-term and long-term drought intensities. The indices for the short-term droughts (ZIND_pm, ZIND_th, SPEI_pm_01, SPEI_th_01, and SM10) all project a weaker drying in the future, while the indices that quantify the long-term droughts (PDSI_pm, PDSI_th, SPEI_pm_12, SPEI_th_12, and SMTC) all project more intense drought in the future (Fig. 2). The ZIND and the 1-month SPEI measure the monthly drought conditions with no memory of the water deficits or surpluses of the previous months. The ZIND and 1-month SPEI are very similar to SM10 in this aspect. Therefore, these short-term drought indices are closely related to precipitation and can change dramatically following precipitation events. The PDSI and 12-month SPEI represent the accumulated water deficit over a long-term period and allow the accumulation of water deficit over time (as available water in the soil profile gets gradually depleted) to be captured, which is a key process in the formation of drought. Thus, these indices are much less affected by short-term moist spells (or by individual major precipitation events), and they allow water deficits to build over time. They are very similar to the SMTC, which also indicates a tendency toward persistent drought in the future. Additionally, the SMTC does not vary from year to year as much in terms of percentage change as that of the SM10 does during the calibration period, so SMTC produces larger negative numbers (more severe drought) for the same percentage changes in the future when normalized. The same mechanism also holds for long-term drought indices.

The spatial distributions of the projected future drought averaged during the 2071–2100 period based on CCSM4 are also analyzed. The forced responses in annual mean precipitation and surface temperature (Figs. 3a,b) are consistent with previous analyses of the CMIP5 climate projections (IPCC 2013; Feng and Fu 2013; Feng et al. 2014; Cook et al. 2014). The annual mean precipitation is projected to increase over the majority of North America except in the southwest United States and northern Mexico. The projected precipitation changes are less than 5% in most of the Great Plains compared to the 1901–2000 climatology (Fig. 3b). On the other hand, all six simulations project increasing temperature. The temperature is projected to
increase by 4.5°C in the southern Great Plains and about 6°C in the northern Great Plains (Fig. 3a). The PE is projected to increase over the entire United States. The changes in PE_th, in particular, are the most obvious, and an increase in PE_th of more than 40% is projected in the Great Plains (Fig. 3d). Larger increases in PE_th are projected in the southern Great Plains (>55%), and slightly weaker increases (>40%) are projected in the northern Great Plains. The variations of PE_th depend on temperature. The impacts of other climate variables (e.g., relative humidity and radiation) on PE_th were empirically calculated based on their relationship with temperature during the instrumental period (Thornthwaite 1948). Changes in these variables would greatly amplify the effect of temperature changes when applied to the nonstationary climate system in the future, thereby leading to high and possibly unrealistic sensitivity of PE_th (Fig. 3c). Unlike the PE_th, the projected changes in PE_pm are not as strong but are still significant, showing about 20%-30% increases in the Great Plains (Fig. 3c). The weaker changes in PE_pm suggest that it is less sensitive to temperature. Scheff and Frierson (2014) identified no more than 3% K⁻¹ changes in PE_pm in the study region due to temperature change alone. Therefore, the projected 4.5°-6.0°C warming in the study region (Fig. 3a) suggest that the temperature would lead to a ~13%-18% change in PE_pm. The remaining ~10% change in PE_pm is caused by changes in other climate variables (e.g., solar radiation, relative humidity, and wind speed). Because the PE_th and PE_pm are projected to increase much faster than the precipitation, the PE-based drought indices are all very similar to the changes in SM10 and show a decline during 2071–2100 (Figs. 4e,i). The projected changes in PDSI_pm and PDSI_th are quite different from the short-term drought indices (Figs. 4d,f). PDSI_pm projects severe to exceptional drought in the southern Great Plains and neutral to moderate drought conditions in the northern Great Plains by the end of this century. When averaged over the entire Great Plains, PDSI_pm projected moderate drought during 2071–2100 (Fig. 2b). PDSI_th, however, projected more severe drought conditions over the United States (Fig. 4f). When averaged over the Great Plains, the projected PDSI_th is lower than ~7.0, much stronger than the most severe drought during 1850–1950 owing to model internal variations (Fig. 2b; Hoerling et al. 2012). SPEI_pm_12 (SPEI_th_12) shows similar results as PDSI_pm (PDSI_th), suggesting persistent drought in the future, especially based on SPEI_th_12 (Figs. 4d,f,h,j).

While all drought indices are qualitatively similar in showing a drying trend in the future, they have different units or use different scales to quantify the drought. Therefore, it is necessary to normalize these indices so that they can be directly compared. We normalized the annual mean drought indices averaged over the Great Plains based on the reference period of 1901–2000. In doing so, all annual time series have a mean of zero and a standard deviation of one during 1901–2000. Those normalized time series are directly comparable and are used to calculate the mean conditions during 2071–2100.

As shown in Fig. 5, the SM10 and SMTC in CCSM4 both exhibit a decline during 2071–2100 compared to the 1901–2000 climatology. The projected changes in SM10 during 2071–2100 are fairly small, and the ensemble mean change is about ~0.7 standard deviations of the typical interannual variability during 1901–2000. This can still be considered as important, and the consequences of such change will likely be considerable as it signals an increase in the frequency of months with lower than usual soil moisture. The projected changes in SMTC during 2071–2100 are larger, with an ensemble mean change of ~1.3 standard deviations of the 1901–2000 climatology. These differences between the SM10 and SMTC are likely caused by their different temporal dynamics, with SM10 being mainly influenced by precipitation. As shown in Table 3, the precipitation can explain about 75% (r = 0.88 during both 1901–2000 and 2001–2100) of the temporal variations of SM10, while it can explain only about 35% (r = 0.59 during 1901–2000 and r = 0.57 during 2001–2100) of the temporal variations of SMTC.

The projected changes in ZIND_pm and SPEI_pm_01 during 2071–2100 (Figs. 4c,g) are very similar to the changes in SM10 and show a slight drying in the Great Plains. Greater changes in ZIND_th and SPEI_th_01 are projected in the Great Plains compared to the PE_pm-based indices (Figs. 4e,i).
FIG. 4. Spatial distribution of the drought indexes changes during 2071–2100 compared to the 1901–2000 climatology based on the simulations of CCSM4. (a),(b) The soil moistures are shown as standardized deviations. For better comparison, (c)–(f) the changes in ZIND and PDSI are shown using the same scales. (g)–(j) The 1-month and 12-month SPEI are also shown using the same scales. The blue rectangle and the hatching are as in Fig.3.
Projected changes in PDSI_pm during 2071–2100 (1.5 standard deviations) are comparable to that of the SMTC (1.3 standard deviations). The changes in SPEI_pm_12 are slightly larger, about 2.0 standard deviations (Fig. 5), possibly because the SPEI is more sensitive to PE changes compared to PDSI (Vicente-Serrano et al. 2015). The drought indices based on the PE_th (PDSI_th, ZIND_th, SPEI_th_01, and SPEI_th_12) all suggest much larger declines in drought intensity than PE_pm based indices or soil moisture values. The projected changes in PDSI_th, in particular, suggested about 5.0 standard deviations of the 1901–2000 climatology, which is far below the most extreme drought event during the twentieth century.

To examine the robustness of drought estimated by PE_pm and PE_th methods, we computed the correlations between the soil moisture and drought indices based on the CCSM4 output (Table 3). As expected, the variations of SM10 are closely related to the short-term drought indices (ZIND_pm, ZIND_th, SPEI_pm_01, and SPEI_th_01) with $r = 0.89$ or higher, whereas the SMTC is strongly correlated to long-term drought indices (PDSI_pm, PDSI_th, SPEI_pm_12, and SPEI_th_12) with $r = 0.78$ or higher during 1901–2000 regardless of the PE methods used. The relationships between SM10 and long-term drought indices are slightly weaker ($r = 0.76$ or lower) especially during 2001–2100, suggesting that it may be problematic to compare the shallow layer soil moisture with the long-term drought indices. However, the correlations between soil moisture and drought indices during 2001–2100 are noticeably different compared to that during 1901–2000 when different PE methods are used to calculate those drought indices. The strong relationships between soil moisture and drought indices based on PE_pm remain nearly unchanged during the twenty-first century compared to that during the twentieth century. For example, the correlations between SM10 and ZIND_pm are 0.94 and 0.93 during 1901–2000 and 2001–2100, respectively. The correlations between SMTC and PDSI_pm are 0.83 and 0.81 during 1901–2000 and 2001–2100, respectively. On the other hand, the relationships between soil moisture and drought indices based on PE_th are appreciably weakened during the twenty-first century. For example, the correlation between PDSI_th and SMTC is 0.78 during 1901–2000, while the correlation changes to 0.58 during 2001–2100. To examine the possible impact of drying trend (Fig. 2) on the correlations between soil moisture and drought indices, we also calculated the correlations after detrending these variables. Our results suggested the correlations between drought

![Fig. 5. Normalized changes in (left to right along the x axis) annual precipitation, soil moisture, and drought indexes averaged over the Great Plains during 2071–2100 compared to the 1901–2000 climatology based on the CCSM4 simulations. All values shown are normalized based on the mean and standardized deviations of the corresponding variables during 1901–2000. As in Fig. 1, the results are plotted with box-and-whisker diagrams representing normalized value changes computed from the six CCSM4 simulations.](image)

Table 3. Correlations between soil moisture and the different versions of PDSI, ZIND, SPEI, and precipitation based on the simulations of CCSM4. The numbers shown are the mean of the six model runs and the one standardized deviation. Numbers in bold indicate that the differences of correlation coefficients between the twentieth and twenty-first century < 0.10.

| Drought indices | SM10 1901–2000 | SM10 2001–2100 | SMTC 1901–2000 | SMTC 2001–2100 |
|-----------------|----------------|----------------|----------------|----------------|
| PDSI_pm         | 0.76 ± 0.04    | 0.71 ± 0.03    | 0.83 ± 0.04    | 0.81 ± 0.07    |
| PDSI_th         | 0.70 ± 0.06    | 0.46 ± 0.05    | 0.78 ± 0.06    | 0.58 ± 0.20    |
| ZIND_pm         | 0.94 ± 0.01    | 0.93 ± 0.01    | 0.77 ± 0.04    | 0.73 ± 0.07    |
| ZIND_th         | 0.91 ± 0.02    | 0.76 ± 0.01    | 0.76 ± 0.06    | 0.65 ± 0.14    |
| SPEI_pm_01      | 0.92 ± 0.01    | 0.86 ± 0.02    | 0.64 ± 0.06    | 0.61 ± 0.10    |
| SPEI_th_01      | 0.89 ± 0.01    | 0.72 ± 0.04    | 0.62 ± 0.07    | 0.53 ± 0.14    |
| SPEI_pm_12      | 0.73 ± 0.04    | 0.64 ± 0.03    | 0.79 ± 0.04    | 0.70 ± 0.13    |
| SPEI_th_12      | 0.72 ± 0.04    | 0.52 ± 0.04    | 0.78 ± 0.05    | 0.57 ± 0.17    |
| Precipitation   | 0.87 ± 0.03    | 0.87 ± 0.02    | 0.59 ± 0.07    | 0.57 ± 0.05    |
indices and soil moisture remain nearly unchanged with and without detrending during 1901–2000. However, the correlations between drought indices and soil moisture become slightly stronger during 2001–2100 after detrending (table omitted). This result suggested that the long-term trend, especially the severe drying trend projected by PE_th-based drought indices during the twenty-first century, would deteriorate the links between drought indices and soil moisture. The PE_th considers monthly mean temperature to be the only driver of PE variations. This method can overemphasize the influence of warmth, and further inaccuracies can be introduced by ignoring the nontemperature components of PE (Hoerling et al. 2012; Sheffield et al. 2012; Williams et al. 2015). Because of the large increase in PE_th, the PDSI_th suggested severe drying, which in turn could deteriorate its link to soil moisture. On the other hand, the robust relationship between PE_pm-based drought indices and soil moisture suggested that it is better to use the physically based PE_pm method to evaluate the future drought variations.

It is also worth noting that the correlations between soil moisture and the PDSI and ZIND are slightly stronger than that of the SPEI, especially during the twenty-first century. This is likely because the PDSI and ZIND are based on soil water balance while the SPEI is based on the statistical distribution of the atmospheric water deficit (precipitation minus PE). Another possible reason is that the soil moisture and PDSI may underestimate the impact of atmospheric evaporative demand on drought severity (Vicente-Serrano et al. 2015).

To verify the results based on CCSM4, we analyzed the soil moisture (SM30 and SM2m) and various drought indices based on the simulations of 25 CMIP5 models. The projected changes in drought risk in the Great Plains during 2071–2100 are shown in Fig. 6. The CMIP5 models projected a slightly increasing precipitation, but all drought indices show a drying trend in the future. The SM30 shows smaller uncertainties (the interquartile range) among the models compared to SM2m. However, the changes in SM30 are slightly larger than SM2m, which is different from the CCSM4 (e.g., SM10 vs SMTC). These differences are likely because different land models with different soil layers and soil physics were used in CMIP5 models. The depths of soil column are also different in SM30 and SM2m (Cook et al. 2015). Despite this minor difference, the projected changes in future drought risk in CMIP5 models are in general similar to the CCSM4. The CCSM4 results are well within the uncertainties (interquartile range) of the CMIP5 simulations, except the SM10 in CCSM4 is weaker than the lower 25% quantile of the SM30. Similar to CCSM4, the projected changes in short-term droughts (e.g., ZIND_pm, ZIND_th, SPEI_pm_01, and SPEI_th_01) during 2071–2100 based on CMIP5 models are overall weaker than the long-term droughts (e.g., PDSI_pm, PDSI_th, SPEI_pm_12, and SPEI_th_12). The changes based on PE_th are stronger than that based on PE_pm. The changes based on PE_pm are similar to soil moisture. On the other hand, the interquartile ranges in future drought changes projected by CMIP5 models are overall larger than CCSM4, suggesting that the intermodel variability in CMIP5 simulations is larger than model variability in single model (CCSM) simulations. Lin et al. (2015) find similar results when comparing CMIP5 models with large ensemble runs made by a single model.

We also computed the correlations between soil moisture and the drought indices based on the CMIP5 models (Table 4). The results are also in general consistent with the CCSM4 (Table 3). The short-term drought indices are closely related to SM30, while the long-term drought indices are closely related to SM2m. The correlations between soil moisture and the PE_pm-based indices are robust in both the twentieth and twenty-first centuries. The correlations between soil moisture and the PE_th-based long-term drought indices (e.g., PDSI_th and SPEI_th_12) in the twenty-first century are noticeably weaker compared to the twentieth century. However, the correlations between other PE_th-based indices and soil moisture are relatively robust during both the twentieth and twenty-first centuries, which are different from that of the CCSM4 (Tables 3 and 4). These differences are likely because different land models were used in the CMIP5 models. Additionally, the SM30 contains lower-frequency variations in soil moisture compared to the SM10, which
may cause the differences between CCSM4 and the CMIP5 models (Tables 3 and 4; Figs. 5 and 6).

### 4. Discussion and conclusions

This study compared multiple drought indices to evaluate why these indices contrast sharply about the future drought risk outcomes in the Great Plains using the output of CCSM4 and 25 CMIP5 models. The water demand (PE) was calculated using the Thornthwaite (PE_th) and Penman–Monteith (PE_pm) methods, which were subsequently used to calculate the drought indices. These drought indices present very different future drought intensities in the Great Plains under climate change. The projected future changes in short-term drought are much weaker (but still very important) compared to that of the long-term drought. Our results also suggest that the disagreements about the future droughts in the Great Plains discussed in previous studies are caused by 1) comparing the projected changes in short-term droughts with that of the long-term droughts (e.g., comparing the SM10 to the PDSI) and/or 2) computing the atmospheric evaporative demand using an empirically based method (e.g., PE_th). The drought indices based on the PE_th method (e.g., PDSI_th, ZIND_th, SPEI_th_01, and SPEI_th_12) all suggest unprecedented future droughts. The PDSI_th, in particular, suggested that the PDSI might be less than −7.0 (about −5.0 standard deviations of the 1901–2000 climatology) by the end of this century, a value far below the most extreme PDSI values during the instrumental period. The temporal variations of PE_th are only related to air temperature, which increase rapidly related to the projected warming (Fig. 2a). As a result, the surface moisture budget is overwhelmed by the strong increase in the PE_th-driven demand. This can also explain why many of the previous studies using PDSI_th projected unprecedented future drought (see Figs. 2, 5, and 6; and also Hoerling et al. 2012). Therefore, the empirically based PE_th, and hence the drought indices based on it (e.g., PDSI_th, ZIND_th, and SPEI_th), should not be used to estimate the responses of drought to climate change, as demonstrated in many previous studies (Donohue et al. 2010; Dai 2011a; Sheffield et al. 2012; Hoerling et al. 2012). However, while the analysis of drought intensity based on the PE_pm method (e.g., PDSI_pm, ZIND_pm, SPEI_pm_01, and SPEI_pm_12) shows seemingly more realistic trends compared to PE_th, these trends are still very unsettling and demonstrate significantly increasing drought risk across the region. The same conclusion holds when the soil moisture is used. When normalized, the ZIND_pm shows similar changes to surface soil moisture, while the PDSI_pm shows similar changes to SMTTC. Our results are also held true in the 25 CMIP5 models.

Because the droughts are usually caused by accumulated water deficits for months to years, this study again suggests the potential for chronic drought across the Great Plains in the future. Cook et al. (2015) suggested that the future drought risk would likely exceed the driest centuries of the Medieval Climate Anomaly (1100–1300 CE) in western North America, leading to unprecedented drought conditions during the last millennium. Ultimately, the chronic drought across the Great Plains (Figs. 4–6) and the American Southwest (Cook et al. 2014, 2015) may represent a substantial challenge for managing the water resources and agriculture in these regions.

It is also worth noting that the increasing CO2 may directly counteract the ecological effects of drought and let the plants survive quite well with less total canopy conductance and/or moisture supply (e.g., Koutavas 2013). Therefore, the variability of soil moisture and drought indices discussed in this study may be less relevant to atmospheric drought stress due to CO2 increase in a future warmer world. Further investigations are needed to examine the interactions between CO2 fertilization and drought impacts.
In summary, our results suggest that the drought indices based on PE_th (PDSI_th, ZIND_th, SPEI_th_01, and SPEI_th_12) lead to severe and unprecedented future drying because the empirical Thornthwaite method is so sensitive to temperature change, especially when applied to the nonstationary climate system in a future warmer climate. To evaluate the future drought conditions, it is better to use the physically based PE_pm method. The drought indices based on PE_pm (PDSI_pm, ZIND_pm, SPEI_pm_01, and SPEI_pm_12) are closely and robustly related to the corresponding soil moisture (e.g., ZIND_pm vs SM10, and PDSI_pm vs SMTC). The short-term drought indices (SM10 and ZIND-PM) all show small but consistent drying trends in the future, while the drought indices that reflect long-term drought (e.g., SMTC and PDSI_pm) suggest moderate to severe drought conditions during 2071–2100. Although this study only focused on the drought in the Great Plains, our techniques could be applied elsewhere around the globe, and there may be other regions where our conclusions may also hold true regarding future drought conditions.

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