Spatial and Temporal Variability of Drought Patterns over the Continental United States from Observations and Regional Climate Models

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ABSTRACT

The aim of this study is to analyze the spatial and temporal structure of drought over the continental United States (CONUS) and their teleconnection at different timescales from observations and climate models. We use the standardized precipitation evapotranspiration index (SPEI) at 12- and 24-month timescales as the drought index. Spatial patterns of drought regimes are delineated by using the principal component analysis (PCA) while the temporal characteristics of the variability of each drought pattern and teleconnection with climate indices are analyzed by using the wavelet analysis. Wavelet coherence of the drought pattern and four climate indices: El Niño–Southern Oscillation (ENSO), Pacific decadal oscillation (PDO), Atlantic multidecadal oscillation (AMO), and North Atlantic Oscillation (NAO) are analyzed. The results show that major drought patterns are located over the Northwest, South, Upper Midwest, and East regions. The spatial pattern of the drought regimes is similar for the 12- and 24-month timescale drought. ENSO influences the drought over West and South at decadal timescales throughout the study period (1950–2015) while intermittent significant coherence is observed at interannual timescale. The coherence of NAO and PDO with SPEI-12 is decreased during recent decades. Generally, regional climate model (RCM)-simulated drought patterns are more localized in a smaller area over the region compared to the spatial extent of observed drought patterns. Power spectra of seasonal to interannual variability (2–5-yr period) of all four drought patterns from RCM simulations are similar to those from the observations. However, at larger periodicities (decadal variations) among-RCM spread increases with increasing periods.

Key words: drought pattern, principal component analysis (PCA), climate teleconnection, wavelet analysis

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1. Introduction

Drought is a condition of below normal water availability over a region compared to the long-term average (or climatology) water availability in the region (Wilhite and Glantz, 1985) that is often triggered due to the natural variability of the climate. Due to its creeping nature, drought is likely to have long-term impacts on several sectors including the economy, health, and environment (Sternberg, 2011). Drought is one of the costliest and widespread natural disasters around the globe (Below et al., 2007; Daryanto et al., 2016; FAO, 2018). Over the continental United States (CONUS), drought is the second most costly natural hazard after tropical cyclones, accounting for greater than 19% of total weather-related disasters in the United States during 1980–2013 (Smith and Katz, 2013; Smith and Matthews, 2015). In addition, climate models have consistently projected increased drought severity and frequency over the CONUS in the warmer climate of the 21st century (Sheffield and Wood, 2008; Dai, 2013).

To facilitate communication, drought is often classified into four types in the literature: 1) meteorological drought (precipitation deficit), 2) agricultural drought (deficit in soil moisture), 3) hydrological drought (streamflow/reservoir level depletion), and 4) socio-economic drought (deficit in economic goods due to droughts). Details on the drought concepts and classifications are given in Wilhite (2000), Mishra and Singh (2010), and Dai (2011). Generally, drought originates from the precipitation deficit due to natural climatic variability (McKee et al., 1993) and propagates to other components of the hydrological cycle such as soil moisture and river flow due to enhanced evapotranspiration and its

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persistance over time (Vicente-Serrano and López- Moreno, 2005; Vicente-Serrano et al., 2010; Dai, 2011; Van Loon and Laaha, 2015). Thus, understanding the controlling factors on the drought onset, persistence, severity, and the spatial–temporal characteristics is of crucial importance for effective drought management.

A great deal of studies have been focused to identify drought patterns and associated climate mechanisms (e.g., Karl and Koscielny, 1982; Namias, 1983; Barlow et al., 2001; Woodhouse et al., 2009). For instance, based on the observed and tree ring-based reconstruction, Woodhouse et al. (2009) identified two leading modes of North American (NA) drought primarily associated with El Niño–Southern Oscillation (ENSO) and Northern Hemispheric annular mode (NAM). Cold sea surface temperature (SST) anomalies over the eastern tropical Pacific called the La Niña phase of ENSO and warm SST anomalies over western Pacific and Indian Oceans are of primary importance in NA drought formation (Hoerling and Kumar, 2003; Cook et al., 2007; Vicente-Serrano et al., 2011). The position of the Rossby wave engendered from the anomalies of the atmospheric general circulation and atmospheric circulation in subtropical and middle latitudes is the most generalized idea of US drought teleconnection (Namias, 1983; Lau et al., 2006; Cook et al., 2007). The tropospheric jet streams move southward during the negative (La Niña) phase of ENSO and deflect the storm tracks that bring extended droughts in the western US (Menking and Anderson, 2003; Brown and Comrie, 2004; McCabe et al., 2004). The Great Plains winter (summer) droughts are associated with the position and strength of the polar jet stream (low-level jet stream) (Woodhouse and Overpeck, 1998; Basara et al., 2013). The jet streams bring the moisture flux to the Great Plains region from the Pacific and the Gulf of Mexico in winter and summer, respectively. The moisture flux and associated drought are linked with the ENSO teleconnections (Schubert et al., 2004; Birk et al., 2010; McCravy and Randall, 2010; Basara et al., 2013). Over the eastern US, northward displacement of jet stream and upper-level westerlies brings dryness in the northern part (Namias, 1983). Droughts in the southeastern region are associated with the changes in the storm genesis and tracks in the North Atlantic and local convection during the warm season and cold fronts during cold seasons (Kam et al., 2013; Kunkel et al., 2013), and the drought characteristics are influenced by atmospheric teleconnections (Namias, 1983; Abiy et al., 2019).

However, the observed drought teleconnection to any single climatic teleconnection index is not consistent, implying that drought generation due to one climatic fluctuation is modulated by other climatic teleconnections (McCabe et al., 2004; Baek et al., 2017; Aryal and Zhu, 2019; Jiang et al., 2019; Parsons and Coats, 2019). For instance, McCabe et al. (2004) showed that Pacific decadal oscillation (PDO) and Atlantic multidecadal oscillation (AMO) are highly correlated with leading modes of interdecadal US drought frequency variability. AMO-induced drought variability is primarily due to the changes in summer rainfall and modulation of the ENSO-induced interannual variability of the winter rainfall (Enfield et al., 2001). PDO modulates the strength of the ENSO-induced dry–wet changes (Wang et al., 2014). A large fraction of drought over the Great Plains is attributed to the variability of ENSO and North Atlantic Oscillation (NAO; Weaver et al., 2009). Thus, the drought events observed in the current climate associated with particular ENSO events may not be identical with those in future ENSO events. One objective of this study is to analyze the climatic teleconnection on the US drought patterns at different temporal scales.

Further, global climate models (GCMs) or regional climate models (RCMs) are often used to project drought scenarios in future climate (Strzepek et al., 2010; Cook et al., 2015; Zhao and Dai, 2015, 2017; Aryal and Zhu, 2017, 2019) and to attribute the causes of climatic variability to natural and/or anthropogenic forcing (Sud et al., 2003; Lambert et al., 2004; Feddema et al., 2005; Stott et al., 2010; Bindoff et al., 2013; Seager and Hoerling, 2014; Wang et al., 2019). Even though climate models have been increasingly used as a drought management planning tool, evaluation of GCMs/RCMs performance to simulate climate variability and its teleconnection still remains an active research topic (e.g., Sheffield et al., 2013; Nasrollah et al., 2015; Ujeneza and Abiodun, 2015; Abatzoglou and Rupp, 2017; Moon et al., 2018). Sheffield et al. (2013) showed that GCMs diverge widely in simulating ENSO teleconnection with the NA climate. Climate models also show significant bias and vary in their ability to reproduce the temporal variability of the teleconnection of North Hemispheric climate (Stoner et al., 2009). Therefore, another aim of this study is to evaluate the performance of RCMs to simulate the CONUS meteorological drought patterns and their periodicities. The methodology and data are described in Section 2 while the results are presented and discussed in Section 3. Section 4 summarizes the findings and concludes the paper.

2. Methodology and data

2.1 Drought index

We use the standardized precipitation evapotranspiration index (SPEI) developed by Vicente-Serrano et al.
(2010) and modified by Beguería et al. (2014) at 12- and 24-month timescales as the drought index. The SPEI is calculated by using the monthly water balance as detailed in Vicente-Serrano et al. (2010). The water balance is the difference between precipitation ($P$) and potential evapotranspiration (PET). We compute the PET using the Penman–Monteith (PM) method. For the observation, PET based on the PM method is available from the Climatic Research Unit (CRU) of the University of East Anglia (Harris et al., 2014) archive. RCMs simulated PET based on PM methods is approximated from minimum temperature, maximum temperature, wind speed, and incoming solar radiation available in Coordinated Regional Climate Downscaling Experiment (CORDEX) archive. We use the Penman function in SPEI library in R (Beguería and Vicente-Serrano, 2017; https://cran.r-project.org/web/packages/SPEI/index.html). To compute SPEI, the cumulative probability (CDF) of the climatic water balance ($P - PET$) of a region is first calculated. The value of the standard normal variate corresponding to the CDF is the value of SPEI. To account for the precipitation/temperature seasonality, the CDF of the climatic water balance is found for each month separately. We compute the PET (ET0) from the Food and Agriculture Organization (FAO) PM method (Allen et al., 1998; Walter et al., 2000). A drought event is identified as any month when SPEI becomes negative. The drought categories based on the SPEI are given in Table 1.

### Table 1. Drought categories defined for different values of SPEI (McKee et al., 1993)

| Drought category   | SPEI value |
|--------------------|------------|
| Mild drought       | $-0.99$ to $0$ |
| Moderate drought   | $-1.49$ to $-1.00$ |
| Severe drought     | $-1.99$ to $-1.50$ |
| Extreme drought    | $\leq -2.00$ |

The PCA transforms one variable into a linear combination that may be also available from another variable. The information available in correlated variables is used to reduce the dimensionality of the data as the first few components explain most of the variances in the dataset. The spatial patterns of the PFs are shown as the PF loadings, which are the correlation coefficients between the variables (SPEI) and PFs. We identify the most dominant modes of variability of drought and regions that show similar drought features in the past based on the PCA (e.g., Woodhouse et al., 2009; Ujeneza and Abiodun, 2015; Asong et al., 2018). The details on the PCA analysis can be found in von Storch and Zwiers (1999) and Maity (2018). We use the PCA with the varimax rotation since it enhances the physical relevance and interpretation of the PCA (Richman, 1986; Jolliffe et al., 2003). We retain four components for the rotation.

#### 2.3 Wavelet analysis

After finding the dominant modes of variability in the dataset, we further perform the wavelet analysis of the PFs to reveal the strength of oscillations at different periods and their temporal variations. We also investigate the co-variability of PFs with the large scale climatic circulation using the wavelet coherence analysis. The wavelet analysis is widely used to study the time series of climate and geophysics in the frequency domain and the details are given in Torrence and Compo (1998). We use the Morlet wavelet as the mother wavelet in the current study (e.g., Schaeffli et al., 2007).

#### 2.4 Data

The study uses the observed gridded precipitation, temperature, wind speed, and radiation data for the CONUS available from the CRU of the University of East Anglia (Harris et al., 2014), which are available from 1950 to 2015 at a 0.5° spatial resolution. We use four climatic indices: ENSO (Trenberth and Hoar, 1996), PDO (Mantua and Hare, 2002), AMO (Kerr, 2000), and NAO (Portis et al., 2001). The 12- and 24-month moving average values of each index are calculated. The indices are obtained from the NOAA Earth System Research Laboratory website (https://www.esrl.noaa.gov/psd/gcos_wgsp/Timeseries). The climate model simulation data are from the six RCMs archived in the CORDEX (Jones et al., 2011). The RCMs used in this study are summarized in Table 2.

### 3. Results and discussion

#### 3.1 The spatial and temporal pattern of CONUS drought

Based on the PCA of the 12- and 24-month SPEI, we identified the regions experiencing similar drought as shown in Fig. 1. The loadings from the corresponding PFs (PF1, PF2, PF3, and PF4) are plotted. The spatial variations of the US drought pattern for the 12- and 24-month timescale SPEI are similar. The cumulative vari-
ability explained by the rotated PF1, PF2, PF3, and PF4 are 10.2%, 21.2%, 29.0%, and 38.3%, respectively, for the 12-month timescale SPEI. For the 24-month timescale SPEI, the cumulative variability explained by the rotated PF1, PF2, PF3, and PF4 are 10.0%, 21.8%, 30.4%, and 41.9%, respectively. The variability explained by the individual PFs for the observations and RCMs is given in Fig. 2. Interestingly, the variability in the CONUS SPEI explained by the first PF is slightly higher for the RCM ensemble compared to that for observations while variability explained by the other PFs is similar for both the RCM ensemble and observations. As shown in Fig. 1, the PFs have different spatial–temporal characteristics. Four dominant modes of SPEI variability are located in Northwest, Southwest and South, central and Upper Midwest, and eastern seaboards. At both timescales, PF1

Table 2. Regional climate models (RCMs) contributing to the Coordinated Regional Climate Downscaling Experiment, North America (CORDEX-NA) analyzed in this study. More details on the RCMs are given in https://na-cordex.org/rcm-characteristics.html

| RCM No. | Driving GCM | RCM          | Resolution (lat × lon) | Historical simulation |
|---------|-------------|--------------|------------------------|-----------------------|
| 1       | GFDL-ESM2M  | RegCM4       | 0.5° × 0.5°            | 1950–2005             |
| 2       | GFDL-ESM2M  | WRF          | 0.5° × 0.5°            | 1950–2005             |
| 3       | HADGEM3ES   | RegCM4       | 0.5° × 0.5°            | 1950–2005             |
| 4       | HADGEM3ES   | WRF          | 0.5° × 0.5°            | 1949–2005             |
| 5       | MPI-ESM-LR  | RegCM4       | 0.5° × 0.5°            | 1949–2005             |
| 6       | MPI-ESM-LR  | WRF          | 0.5° × 0.5°            | 1950–2005             |

Fig. 1. The spatial pattern of the 12-month (top) and 24-month (bottom) SPEI variability over the CONUS during 1950–2015. The corresponding loadings of each principal factor (PF) are plotted.

Fig. 2. Scree plot depicting the variances explained by the individual PFs for SPEI-12 and SPEI-24 over the CONUS. The solid dark line represents the observed SPEI while dashed line represents the RCM ensemble. The green lines are for individual RCMs.
and PF2 show relatively strong Pacific northwest–south dipole patterns of variability and are well characterized as the ENSO imprint of the western US drought in the literature (Dettinger et al., 1998; Cayan et al., 1999; Woodhouse et al., 2009). Similar to PF1, PF2 also shows north–south dipole; however, the strength of dipole is weak. Winter drought in western North America is primarily due to the reduced precipitation (Namias, 1983). While the interannual variability of the drought in the western region is due to ENSO variability, interdecadal variability is correlated with the PDO and AMO (McCabe et al., 2004; Jiang et al., 2019). For instance, Ji-ang et al. (2019) showed that AMO+/PDO− phase brings prolonged drought over the western US. Similarly, PF3 that explains ~21% of the total variability in the CONUS SPEI shows higher loadings in the Great Plains and Midwest regions. Drought in this region is found to be strongly linked with the SST anomalies in the tropical Pacific that affect Great Plains precipitation. The land-atmospheric coupling also explains a large fraction of drought variability over the region (McCrary and Randall, 2010). PF4 shows a strong correlation in the eastern US where drought is influenced by Pacific and Atlantic oceanic conditions (Namias, 1983).

We further perform the wavelet analysis to examine the periodicities of the drought modes. The wavelet power spectrum and the global power spectra of the PF scores (time series of the PFs) for the 12-month SPEI are shown in Fig. 3. PF1 and PF4 that have higher loadings in Northwest and East respectively show higher peaks in the global power spectra at 75- and 220-month (~5–15 yr) periods even though the power of PF4 spectra is small. The interannual and interdecadal variability of the drought over the regions might be attributed to the ENSO and PDO influences (McCabe et al., 2004, 2008).

For all PF1, PF3, and PF4, significant periodicity at ~5–6 yr is not stationary particularly during the 1960s. For PF2, decadal-scale variability (~128–256 months) periodicity is not significant around the 1980s. The wavelet power spectrum and global power of 24-month SPEI (Fig. 4) is generally similar to that of 12-month SPEI. However, the strength of the periodicity or global

![Fig. 3. Wavelet power spectrum (using Morlet wavelet) and global power spectra averaged over time for different periods for the PFs of SPEI-12. Hatched areas indicate cone of influence where values may be influenced from the edge effects. Black contours show the 95% confidence level.](image-url)
power spectrum of SPEI-24 for all four drought patterns tends to be lower (higher) in interannual (decadal) variability than that of the SPEI-12.

3.2 The teleconnections of the drought patterns

We analyze the wavelet coherence between each PF score and climatic indices to see significant co-variability and temporal changes in the co-variability and the results are shown in Figs. 5, 6. It is apparent that PF1 and PF3, which have the highest loading on the Northwest and Midwest US, show a strong correlation with the ENSO at around 5–7- and 10-yr periods. ENSO influence is generally interannual (1–7 yr). We attribute the observed correlation at ~10-yr period to the influence of other climatic teleconnections to the ENSO-related variability as discussed in Aryal and Zhu (2019) and Asong et al. (2018). On the other hand, PF2 and PF4, which have the highest loadings in the South and eastern regions respectively, show significant coherence with the ENSO at interannual periods. PDO shows significant coherence at interannual and decadal timescales (12–15 yr) with PF1 (Northwest) and PF2 (South). PDO also shows multi-

3.3 Correlations of drought patterns with meteorological variables

To understand the relative role of different meteorological variables to the variability of major drought patterns, we compute the correlation coefficient between the PF scores and five meteorological variables, and the results are shown in Fig. 7. The moving sum (for precipitation and potential average) or moving average (for maximum and minimum temperature) is correlated with the PF scores of each pattern. The correlation coefficients

Fig. 4. As in Fig. 3, but for SPEI-24.
As expected, all four drought patterns are positively correlated with SPEI-12 and negatively correlated with PET, minimum temperature ($T_{\text{min}}$), and maximum tem-
perature ($T_{\text{max}}$). SPEI and precipitation show the strongest correlation with PF1 (Northwest), while PET shows a strong correlation with PF2 (South). The drought variabilities in the northern Rockies (PF3) and central...
Ohio Valley (PF4) are not correlated with temperatures, implying that factors other than temperature (such as wind speed, radiations) might be responsible for the drought variability associated with PET variability in the region (Vadeboncoeur et al., 2018). The correlation of SPEI-24 drought patterns with the meteorological variables (figure omitted) is similar to that with SPEI-12.

3.4 RCM-simulated drought patterns

Figures 8 and 9 show the spatial–temporal pattern of the CONUS drought simulated by the six regional climate models at 12- and 24-month timescales, respectively. In general, all RCMs reproduce four major drought patterns over the CONUS at both timescales. This shows the robustness of the observed drought patterns over the CONUS. Some noticeable differences, however, exist in the simulated patterns compared to those from the observations. For instance, PF2 is more localized in small regions over the South extending northwards to the interior regions. PF3 is located more westwards compared to that in the observations. The RCM1, RCM2, and RCM3 consistently show a strong Southeast–Upper Midwest dipole that is not present in the observations. Comparing the RCM spread shown in Figs. 8, 9 finds that RCMs are more consistent in simulating 24-month timescale drought than 12-month timescale drought.

The CONUS has experienced severe and persistent drought in the arid western states and also in the relatively humid eastern states. Tree-ring-based drought reconstruction shows the severe drought in the South and Southwest during the 13th century and in the Mississippi Valley during the 14th, 15th, and 16th centuries.
During the last century, the 1930s “Dust Bowl” and 1950s Southwest drought are the prominent multiyear persistent droughts (Fye et al., 2003). In addition, the 1988 western US drought (Trenberth et al., 1988) and 1993 southeastern drought (Lott, 1994) were also widespread and severe. As a case study, using the 12-month timescale SPEI, we briefly analyze and discuss how well the drought pattern from the observations and RCMs reflects the multiyear persistent south and southwestern drought of the 1950s.

From Figs. 1, 7, the PF2 has the highest loadings over the South and Southwest. Time series plot of the PF2 from SPEI-12 is shown in Fig. 10. The PF2 from observed SPEI is persistently negative until 1957, implying persistent drought, and the results are consistent with Fye et al. (2003). The differences among the RCMs and observations can be generally seen from the results. The RCMs show a large negative score (droughts) with frequent switching to positive (implying wet spells). The differences might be due to the spin-up period for the
first few years that affects the ability of RCMs to simulate complex processes such as regional soil moisture equilibrium and associated feedbacks realistically (Yang et al., 2011; Jerez et al., 2020). The spin-up period of the RCMs are: RegCM4—1 yr and WRF—2.5 yr. In addition, the RCMs driven by GCMs are generally able to capture the statistics of the observations rather than the time-to-time sequence (Maraun et al., 2010).

We further compute the global power spectra of the RCM-simulated four drought patterns and the results are shown in Figs. 11, 12 for SPEI-12 and SPEI-24, respectively. All RCMs simulate the general pattern of power spectra until 2–5-yr period.

Fig. 9. As in Fig. 8, but for the 24-month SPEI variability based on RCM-simulated SPEI-24.

The strength of interannual periodicity of the drought pattern PF1 that has higher loading in Northwest is overestimated by all six RCMs for both 12- and 24-month timescales. At higher periodicities (> 5–7 yr), the power spectra simulated by individual RCMs diverge widely with the observed spectra nearly at the mean of RCM simulations. Previous studies (e.g., Syed et al., 2014) have shown that the RCM biases in the mean state and interannual variability of precipitation and temperature
are primarily due to the systematic biases in the RCM physical parameterizations that are independent of the driving GCMs. The RCM deficiencies in simulating low-frequency variability might be attributed to the biases in the driving GCMs and the relatively short period of data to capture multidecadal scale variability and trends (de Elía et al., 2013).

The correlations between the RCM-simulated drought patterns and key meteorological variables are shown in Fig. 13. Overall, the RCMs simulate the observed correlation of meteorological variables with major drought patterns. Some remarkable deficiencies in the RCM simulations, however, exist. For instance, the RCM simulations do not show the observed strong correlation of Northwest (PF1) drought variability with temperature. Similarly, over northern Rockies, RCM-simulated drought variability shows similar correlations with the PET, maximum temperature, and minimum temperature, while the observed drought variability in the region associated with the PET variability is primarily due to factors other than temperature.

Understanding the spatial and temporal variability of drought improves the predictability of regional drought. In addition, analysis of climate model ability to reproduce observed drought patterns helps to accurately predict future drought scenarios and hence reduce the risk associated with drought occurrence. The combination of six RCMs analyzed in this study comprises two RCMs (RegCM4 and WRF) driven by three different GCMs (GFDL-ESM2M, HADGEM3ES, and MPI-ESM-LR). Previous studies have shown the relative importance of GCMs and RCMs to reproduce drought variability at dif-

Fig. 10. Timeseries of PF2 that has the highest loading over the southern CONUS from the observations and RCMs. Negative values indicate drought conditions. Details on the RCMs are given in Table 2.
Fig. 11. Global power spectra of four major drought patterns: PF1, PF2, PF3, and PF4 based on SPEI-12 from the observations and RCM ensemble. The broken lines show the range of RCM simulations.

Fig. 12. As in Fig. 11, but for SPEI-24.

Different temporal scales over North America (Ault et al., 2012; Kravtsov et al., 2018; Crhová and Holtanová, 2019; Prein et al., 2019). For instance, Prein et al. (2019) concluded that GCM selection is crucial in simulating a balance between weather type in the large domain and realistic representation of mesoscale variability in smaller domain weather types while RCMs better represent variability within a weather type. Similarly, Crhová and
Holtanová (2019) showed that temperature variance is better reproduced by RCMs and the results are inconsistent in the case of precipitation. In our study, results do not show any systematic improvement in the climate model simulated SPEI variability from any particular RCM/GCM combination.

4. **Summary and conclusions**

In this study, we analyze the spatiotemporal variability of the US drought at different temporal scales from the observations and RCM simulations. Drought is characterized by using the standardized precipitation evapotranspiration index (SPEI) at 12- and 24-month timescales. Four dominant patterns of US drought are identified based on the rotated PCA of the 12- and 24-month SPEI from both the observations and RCM simulations. Temporal variance in the drought patterns and teleconnection with four climatic indices (ENSO, PDO, NAO, and AMO) are explored by the wavelet analysis. The findings of the study are summarized as follows:

1. About 38% of the total variance in the 12- and 24-month timescale SPEI over the CONUS for 1950–2015 can be explained by the first four major drought patterns.

2. The four major drought regimes are located over the Northwest, South, Upper Midwest, and East regions, respectively. The spatial pattern of drought regimes for the 12- and 24-month timescales is similar. However, the strength of variability of 24-month SPEI is higher (lower) than that of 12-month SPEI for decadal (seasonal to interdecadal) variability.

3. Climatic teleconnections of SPEI with climatic in-
dices (ENSO, PDO, NAO, and AMO) are similar for 12- and 24-month SPEI. Intermittent significant coherence with ENSO is observed at interannual timescale. We also observed the significant correlation with ENSO over the West (PF1) and Midwest (PF3) at around 10-yr period during the 1980s. The coherence of NAO and PDO with SPEI-12 is decreased during recent decades. AMO shows strong interdecadal correlation over the South region.

(4) All six RCMs analyzed in this study simulate spatial patterns of four drought modes similar to those from the observations. Generally, RCM-simulated drought patterns are more localized in smaller areas over the region compared to the spatial extent of observed drought patterns.

(5) Power spectra of seasonal to interannual variability (2–5-yr period) of all four drought patterns from the RCM simulations are similar to those from the observations while at larger periodicities (decadal variations) among-RCM spread increases with increasing periodicities.

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