Elucidating Diverse Drought Characteristics from Two Meteorological Drought Indices (SPI and SPEI) in China

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ABSTRACT

This study elucidates drought characteristics in China during 1980–2015 using two commonly used meteorological drought indices: standardized precipitation index (SPI) and standardized precipitation–evapotranspiration index (SPEI). The results show that SPEI characterizes an overall increase in drought severity, area, and frequency during 1998–2015 compared with those during 1980–97, mainly due to the increasing potential evapotranspiration. By contrast, SPI does not reveal this phenomenon since precipitation does not exhibit a significant change overall. We further identify individual drought events using the three-dimensional (i.e., longitude, latitude, and time) clustering algorithm and apply the severity–area–duration (SAD) method to examine the drought spatiotemporal dynamics. Compared to SPI, SPEI identifies a lower drought frequency but with larger total drought areas overall. Additionally, SPEI identifies a greater number of severe drought events but a smaller number of slight drought events than the SPI. Approximately 30% of SPI-detected drought grids are not identified as drought by SPEI, and 40% of SPEI-detected drought grids are not recognized as drought by SPI. Both indices can roughly capture the major drought events, but SPEI-detected drought events are overall more severe than SPI. From the SAD analysis, SPI tends to identify drought as more severe over small areas within 1 million km² and short durations less than 2 months, whereas SPEI tends to delineate drought as more severe across expansive areas larger than 3 million km² and periods longer than 3 months. Given the fact that potential evapotranspiration increases in a warming climate, this study suggests SPEI may be more suitable than SPI in monitoring droughts under climate change.

1. Introduction

China is one of the major “hot spots” for high-intensity droughts and has suffered from large drought-induced socioeconomic losses over the past several decades (Zhai et al. 2010; Wang and Chen 2014; Yu et al. 2014; Herrera-Estrada et al. 2017). The average drought-related economic loss is approximately 35% of the total losses

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related to natural disasters in China (Song et al. 2003). The vulnerability to droughts is especially highlighted because 22% of the world's population is fed by only 7% of the world's arable land there (Zhang et al. 2010). For example, droughts that occurred in 1999–2000 over northern China and in 1997 and 2008–09 over southern China caused massive damage to agriculture and natural ecosystems (Liu and Zhang 2002; Gao and Yang 2009). The extreme drought event in southern China during 2009–10 led to nearly 30 billion U.S. dollars in economic losses, and over 16 million people and 11 million livestock were without a sufficient supply of drinking water (Lu et al. 2011; Yang et al. 2012). Drought is expected to become more severe, prolonged, and frequent under future climate projections (Qiu 2010; Dai 2013; Leng et al. 2015). Therefore, a better understanding of drought characteristics is crucial for monitoring and forecasting drought and ultimately providing reliable strategies to adapt to drought hazards.

Drought naturally occurs over spatially adjacent areas and temporally continuous periods. However, these interrelated spatial–temporal characteristics of drought are often negligibly examined (Lloyd-Hughes 2012; Haslinger and Blöschl 2017), for example, focusing only on the temporal variation of regionally averaged drought variables over a particular spatial extent and/or the spatial pattern of drought temporal change during a specific period (Patel et al. 2007; van der Schrier et al. 2007; Sheffield and Wood 2008; Mishra and Singh 2010). These studies may miss relevant information on drought dynamics by artificially separating the closely interrelated spatial and temporal drought structures (Lloyd-Hughes 2012; Xu et al. 2015). To address this problem, Andreadis et al. (2005) proposed a severity–area–duration (SAD) approach based on three-dimensional structures (i.e., latitude, longitude and time), which simultaneously considers drought interrelated spatial–temporal characteristics and provides comprehensive assessments of drought spatiotemporal dynamics (Sheffield and Wood 2007; Sheffield et al. 2009; Wang et al. 2009; Vidal et al. 2010; Xiao et al. 2016; Zhan et al. 2016; Zhai et al. 2017).

Meteorological indices are widely used to study drought at both the regional and global scales (Vicente-Serrano et al. 2015; She and Xia 2018), considering high-quality meteorological data that are widely available and often less entangled with anthropogenic signals (e.g., land use transformation, Li et al. 2015). Among them, the standardized precipitation index (SPI; McKee et al. 1995) and the standardized precipitation evapotranspiration index (SPEI; Vicente-Serrano et al. 2010)

are two of the most extensively used ones. The SPI has been extensively utilized in previous studies for its ease of computation and its ability to detect drought at multiple time scales (e.g., He et al. 2011; Gocic and Trajkovic 2013; Diffenbaugh et al. 2015; Farahmand and AghaKouchak 2015; Li et al. 2019). The SPI solely considers precipitation and relies on two assumptions: 1) the variability of precipitation is much higher than that of other variables, such as temperature and potential evapotranspiration (PET); and 2) the other variables have negligible temporal trends (Vicente-Serrano et al. 2010). However, these assumptions are challenged under climate change, which is characterized by increasing temperature and atmospheric evaporative demand (Sheffield and Wood 2008; Vicente-Serrano et al. 2014; Milly and Dunne 2016). Previous studies have shown that both temperature and precipitation play an important role in drought response (Dai et al. 2004; Hu and Willson 2000; Trenberth et al. 2014). In this context, the SPEI was developed using the climatic water balance concept of climatic water supply and atmospheric evaporative demand (Vicente-Serrano et al. 2010). The SPEI considers the sensitivity of the atmospheric evaporative demand to drought, as caused by fluctuations and trends in climatic variables other than precipitation, which could better capture the drought dynamics than the SPI over regions with increasing temperature and PET (McEvoy et al. 2012; Vicente-Serrano et al. 2014; H. Wang et al. 2015).

Both the SPI and SPEI have been widely used to study meteorological droughts over China (Xu et al. 2015; Chen and Sun 2015; W. Wang et al. 2015; Yao et al. 2018), whereas the differences in drought characteristics detected by them in China have still not been comprehensively assessed. This study aims to provide a comprehensive assessment of the drought spatiotemporal dynamics between the SPI and SPEI in mainland China and to understand the impact of atmospheric water demand on drought in a climate change context. We choose a 36-yr period from 1980 to 2015, during which time drought became more frequent and severe in China (Ren et al. 2012; Li et al. 2017; Shao et al. 2018). We first analyze the drought temporal change to gain the overall difference between the SPI and SPEI. Individual drought events are then identified using the three-dimensional clustering algorithm. We finally use the SAD method to examine the interrelated spatial and temporal characteristics of the identified drought events. Our dataset and methodology are described in section 2. Section 3 presents a detailed comparison between the SPI- and SPEI-identified drought as outlined above. Finally, the

discussion and conclusions are given in [section 4](#) and [section 5](#), respectively.

2. Data and methodology

a. Dataset

This study focuses on drought analyses in mainland China from 1980 to 2015. The monthly gridded precipitation P with a spatial resolution of $0.5^\circ \times 0.5^\circ$ is obtained from the National Meteorological Information Center (<http://www.nmic.cn/>), which is processed based on gauged precipitation with extensive quality controls (Wu and Gao 2013; Zhou et al. 2015). The PET is calculated based on the China Meteorological Forcing Dataset (CMFD) using the Food and Agricultural Organization (FAO) Penman–Monteith method (FAO-PM; Allen et al. 1998). The CMFD was produced by merging a variety of data sources and is widely used for land surface modeling and data assimilation (Yang et al. 2010; Chen et al. 2011). The obtained daily CMFD dataset has a spatial resolution of $0.1^\circ \times 0.1^\circ$. The data are first aggregated into a spatial resolution of $0.5^\circ \times 0.5^\circ$, then used to calculate the daily PET and finally summed up to obtain the monthly PET. Compared to another widely used Climatic Research Unit (CRU, Harris et al. 2014) PET data, CMFD-based PET shows better consistency with the station-based PET in mainland China (section S1 in the online supplemental material). The FAO-PM method is a physically based model considering temperature, wind, humidity, and solar radiation. Therefore, it can comprehensively reflect changes in multiple atmospheric variables on PET.

The standardized P (P_{std}) and standardized PET (PET_{std}) are also computed following a similar process. At each grid, the P_{std} is calculated for each monthly time step i :

$$P_{\text{std}}(i) = \frac{P(i) - \mu(m)}{\sigma(m)}, \quad (1)$$

where $P(i)$ is the P at time step i (corresponding to month m); $\mu(m)$ and $\sigma(m)$ are the mean and standard deviation of the annual P time series for month m (from January to December). The PET_{std} is calculated following the same process.

Both the SPI and SPEI are used to quantify the meteorological drought, which are calculated following McKee et al. (1995) and Vicente-Serrano et al. (2010), respectively. The SPI uses the two-parameter Gamma distribution to fit the cumulative monthly precipitation time series. Calculation of the SPEI is similar to that of the SPI: replace the variable of precipitation with the

cumulated difference between the monthly P and PET, i.e., the climatic water surplus/deficit, and then fit the data by the three-parameter log-logistic distribution. Both indices use the probability density functions to fit the time series (P for SPI and $P - PET$ for SPEI) and then use the inverse standard normal distribution to transfer the cumulative probability density functions to the drought index value. Positive/negative values of the SPI and SPEI indicate wet/dry conditions. In this study, the threshold value of -1 is used to distinguish a drought event following Xu et al. (2015). The 3-month time scale is used to characterize drought events for both the SPI and SPEI (Xu et al. 2015). A long-term time scale (>3 months) or a short-term time scale (<3 months, e.g., time scale for flash drought) is not considered here (Zhao et al. 2015; Wang et al. 2016).

Monthly drought statistics are calculated to analyze the overall drought temporal change (section 3a). The monthly drought area is the sum of the drought grid areas for each month. The monthly drought combined metric is computed as the sum of the production of severity (i.e., the absolute value of the SPI/SPEI) and area in each drought grid across all drought grids for each month (Sheffield et al. 2009; Wang et al. 2011).

b. Drought clustering algorithm

We use the three-dimensional (i.e., latitude, longitude, and time) clustering algorithm proposed by Andreadis et al. (2005) and further developed by Lloyd-Hughes (2012) to cluster the drought grids into individual drought events, which are adjacent in space and continuous in time.

- 1) Extracting spatially adjacent drought clusters in the study area for each month. Grids defined as drought ($\text{SPI or SPEI} \leq -1$) are clustered with their spatially neighboring drought grids. Whether two drought grids are considered neighboring grids depends on the number of grids between them, i.e., the so-called cell spatial radius R (i.e., R_{lat} and R_{lon}) defined by Lloyd-Hughes (2012). $R = 0$ means that neighboring grids share a common boundary or vertex. The radius $R = 1$ means the distance between neighboring cells should be no more than one grid (illustrated in Fig. 1 of Lloyd-Hughes 2012). Then, drought grids are classified into different drought clusters. As we focus mainly on large-spatial-scale droughts, drought clusters with areas less than a *spatial coherent area threshold* (θ_s) are eliminated.
- 2) Connecting the identified drought clusters across continuous months. Considering two continuous months, if any pair of drought clusters between the two months have an overlap area larger than a

temporal overlap area threshold (θ_T), then these two drought clusters belong to the same drought event. This step is repeated for all months to identify all individual three-dimensional drought events.

Here, we set R_{lat} and R_{lon} to 1 to avoid data gaps commonly seen in observations (Lloyd-Hughes 2012). To avoid the issue of some incorrect long-lasting droughts with tenuous spatial connectivity (Sheffield et al. 2009), both θ_S and θ_T are set to 150 000 km² (approximately sixty $0.5^\circ \times 0.5^\circ$ grids), which was proved to be suitable for drought identification in China (Wang et al. 2011).

c. Drought event statistics

The statistics of the identified individual drought events are calculated, including the drought duration, affected area, volume, and combined metric. Drought duration is the persistent time of a drought event. The affected area is the grid area swept by a drought event. The drought volume (unit: km² month) equals the sum of the production of drought area and the time length (i.e., 1 month) in each grid across all grids of a drought event. The drought event combined metric is computed as the sum of the production of severity (i.e., the absolute value of the SPI/SPEI) and the area of each grid across all drought grids for an individual drought.

d. Severity–area–duration analysis

To jointly analyze the drought severity, spatial patterns, and temporal evolution, Andreadis et al. (2005) developed a severity–area–duration method, which is based on three-dimensional drought structures and intrinsically considers drought interrelated spatial and temporal characteristics. The SAD method was adapted from the depth–area–duration (Grebner and Roesch 1997) method, which is widely used to characterize storm precipitation (WMO 1969). Instead of using the soil moisture percentile in Andreadis et al. (2005), we use the meteorological drought index (MDI, i.e., SPI or SPEI) to define the severity $S = \sum MDI/t$, i.e., averaged MDI over t months. Parameter t is set to a given time length or duration, i.e., 1, 2, 3, 6, 9, and 12 months. The D in the SAD method is a given specific period to analyze the drought dynamics, which should not be confused with the duration of a given drought event. For example, if the duration (i.e., the total time length) of a given drought event is 12 months. During the SAD method, D ranges from 1 month, 2 months, 3 months, ..., up to 12 months. Similarly, the S in the SAD method is also a range of area values.

Based on the drought grids extracted as presented in section 2b, each grid's S is then averaged over a given series of drought affected areas A starting from 30 grids

(approximately 75 000 km²) with increments of 20 grid cells (approximately 50 000 km²). Within the temporal and spatial extension of each drought event, we calculate a series of averaged severities S at a given duration D and a given area A and then draw the SAD curves. The SAD analysis offers a relatively objective way to compare drought events. More detailed descriptions of the SAD method can be found in Andreadis et al. (2005) and Lloyd-Hughes (2012). The SAD method can provide a relatively objective and comprehensive way to simultaneously access the drought spatiotemporal dynamics of severity, area, and duration.

3. Results

a. Overall temporal drought change

Figure 1 shows the temporal variation in the domain-averaged P_std and PET_std , the total drought area, and the monthly combined metric over mainland China from 1980 to 2015. We split the entire period into two sub-periods: the first 18 years (i.e., F18y, from 1980 to 1997) and the most recent 18 years (i.e., R18y, from 1998 to 2015). The average difference between P_std over F18y and R18y is nonsignificant (Fig. 1a, red dashed lines), which suggests that the P -determined SPI-detected drought shows a nonsignificant difference between F18y and R18y from the perspective of the drought area and combined metric (Figs. 1b,c). By contrast, the PET_std shows a significant increase in R18y compared to that in F18y (Fig. 1a, blue dashed lines). The SPEI delineated drought area and combined metric also significantly increase in R18y (Figs. 1b,c). Although the climatic water supply (i.e., P) and its characterized droughts did not change much in the past 36 years, as additional increasing atmospheric evaporative demand (i.e., PET) is considered, the SPEI-detected drought significantly becomes more severe over R18y ($p < 0.05$ with Student's t test). It is notable from Fig. 1 that P is not sufficient to characterize the meteorological drought change in mainland China, and PET plays a dominant role in the meteorological drought under warming periods.

b. Spatial patterns of drought change

We further analyze the spatial patterns of temporal changes in the P_std and PET_std , SPI, and SPEI between F18y and R18y (Fig. 2). The spatial pattern of the P_std change is consistent with that of the SPI (Pearson correlation coefficient equals 0.99, Fig. 2e). The P_std and SPI show increases in two-thirds of mainland China, particularly over the northwestern and northern parts, whereas they show decreases in southwestern China (Figs. 2a,c). In total, 22.95% of the regions show a

FIG. 1. Temporal variations in the (a) domain-averaged standardized P (denoted as P_std) and standardized PET (denoted as PET_std), (b) total drought area, and (c) monthly combined metric as a monthly time series (denoted as mon), 13-month moving average (denoted as 13-mon_avg), and the first and most recent 18-yr average (denoted as 18-year_avg).

significant SPI increase and drought relief ($p < 0.05$, Student's t test). By contrast, most regions show significant increases in PET_std and, consequently, more severe droughts detected by the SPEI in R18y (Figs. 2b,d). Similar patterns are found for the drought occurrence frequency (section S2 in the supplemental material). A decreasing drought frequency is detected by the SPI, but an increasing drought frequency is detected by the SPEI. It is apparent that the changes in PET, rather than P , dominate the spatial pattern changes in the SPEI (Fig. 2f).

c. Characteristics of identified drought events

The previous analysis shows different patterns of drought temporal changes between the SPI and SPEI and highlights the importance of PET for the meteorological drought analysis under a warming climate. In the following sections, we further investigate the three-dimensional structures of drought events to gain more insights into the different drought characterizations outlined earlier. During the drought event identification

(see details in section 2b), some of the drought grids were eliminated. SPEI droughts still have larger areas than SPI droughts after event identification (Fig. S3 and Table S1 in the supplemental material).

1) DROUGHT EVENT IDENTIFICATION

Table 1 summarizes the statistics of individual drought events identified using the three-dimensional clustering algorithm. A greater number of drought events are identified by the SPI than by the SPEI. Especially for the events lasting ≤ 2 months, the SPI identifies 325 events, but the SPEI identifies only 202 events (section S2 in the supplemental material). However, the SPEI detects more drought grids and corresponding drought areas than does the SPI. Therefore, on average, the drought events identified by the SPI are smaller, regarding the grid number and area, than those identified by the SPEI.

There is a large difference in detected drought grids between the two indices. Approximately 30% (i.e., $100\% - 68.71\%$) of the SPI-detected drought grids are not identified as drought by SPEI, and 40% of the

FIG. 2. A comparison of the monthly averages between R18y and F18y of the (a) standardized P (denoted as P_{std}), (b) standardized PET (denoted as PET_{std}), (c) SPI, and (d) SPEI. Spatial relationships of the difference in (e) P_{std} vs SPI and (f) P_{std} vs SPEI (red circles) and PET_{std} vs SPEI (blue circles) between R18y and F18y. The “ Δ ”/“ ∇ ” denote the percentage of grids with an increasing/decreasing pattern. The stippling indicates the regions with a significant difference in averages between R18y and F18y (Student’s t test, $p < 0.05$). The “ r ” denotes the Pearson correlation coefficients.

SPEI-detected drought grids are not recognized as drought by SPI. For events lasting at least 3 months (section S2 in the supplemental material), Approximately 50% of the SPEI-detected drought grids are not identified as drought by SPI, and 30% of the SPI-detected drought grids are not recognized as drought by SPEI. These differences between identified drought events highlight the crucial role of increasing PET, considered in the

SPEI but not in the SPI, in characterizing meteorological droughts.

2) DROUGHT EVENT STATISTICS

Figure 3 shows the drought duration, affected area, volume, and drought event combined metric as bar charts, revealing a general high consistency between the SPI and SPEI. These statistics show that there are many

TABLE 1. Summary of identified three-dimensional events.

	SPI	SPEI
Total number of events	431	301
Total number of grids (10^4)	19.45	22.23
Consistent drought grid number identified by SPI and SPEI (10^4)	13.37	
Percentage (%)	68.71%	60.13%
Total area (10^7 km 2)	47.67	54.47
Consistent drought area identified by SPI and SPEI (10^4)	33.06	
Percentage (%)	69.35%	60.69%

small drought events and few large drought events. Compared to the SPI, the SPEI identifies a greater number of large events but a smaller number of small events in terms of drought event duration, affected area, volume, and drought combined metric.

3) MAJOR DROUGHT EVENTS

Table 2 lists the top twenty droughts ranked by the drought combined metric. We use the same labels (“a”–“t”) to mark the drought events to indicate when the events occurred in approximately the same period and the same region. Eighty percent (16 out of 20) of the events have the same labels, which indicates that the SPI and SPEI have similar capabilities in capturing major drought events. Among these 20 events, more

events are detected by the SPEI (i.e., 13 events) than are detected by the SPI (i.e., 11 events) during the most recent 18 years (1998–2015), indicating that the SPEI can better show the trend of large events becoming more frequent under a warming context.

Drought events detected by the SPEI are generally more severe than those detected by the SPI, in terms of the drought affected area, drought volume, and drought combined metric, and generally longer in duration (Fig. 4). Ten out of 20 SPEI identified events correspond to multiple SPI identified droughts, whereas only one-quarter of the 20 SPI-based events correspond to multiple SPEI-based events. For example, the SPEI-m drought (June 2014–December 2015) corresponds to the SPI-m drought (May 2015–November 2015) and three other SPI-based droughts (not listed in Table 2).

4) DROUGHT EVENT DEMONSTRATION

The evolution of two drought events (labeled “e” and “g” in Table 2) is presented in Figs. 5 and 6 to further demonstrate the drought difference identified by the SPI and SPEI. Drought-e denotes the 1998–99 northern China drought, which caused serious socioeconomic damage. Spatially, both SPI-e and SPEI-e well capture this major drought center in the north and another smaller drought center in the south. Temporally, the north drought center originates from the central north of

FIG. 3. Statistics summary of identified three-dimensional drought events: (a) drought duration, (b) drought area, (c) drought volume, and (d) drought event combined metric. Note that the y axis is irregularly spaced; r is the Pearson correlation coefficient of statistics between the SPI and SPEI.

TABLE 2. Top 20 drought events ranked by combined metric.

Drought rank	Label	Period	SPI-based drought			SPEI-based drought				
			Affected area (10 ⁶ km ²)	Drought volume (10 ⁷ km ² month)	Combined metric (10 ⁷ km ² l)	Label ^a	Period	Affected area (10 ⁶ km ²)	Drought volume (10 ⁷ km ² month)	Combined metric (10 ⁷ km ² l)
1	a	December 1983– December 1984	7.27	1.87	2.86	m	June 2014– December 2015	8.08	3.31	4.96
2	b	December 2010– November 2011	4.09	1.33	2.42	c	December 2000– April 2002	6.94	2.88	4.29
3	c	April 2001– November 2001	5.26	1.34	2.08	e	September 1998– December 1999	7.05	2.35	3.65
4	d	November 1996– December 1997	4.63	1.23	1.91	—	October 2008– March 2010	6.38	2.31	3.37
5	e	October 1998– April 1999	3.66	1.08	1.86	—	March 2006– August 2007	5.70	1.88	2.63
6	f	March 1995– September 1995	4.57	1.08	1.75	g	September 2009– July 2010	4.08	1.56	2.35
7	g	September 2009– April 2010	3.83	1.03	1.68	—	February 2004– September 2004	5.92	1.51	2.23
8	h	February 1987– December 1987	4.05	0.87	1.33	b	December 2010– November 2011	3.92	1.34	2.13
9	i	December 2012– May 2013	4.00	0.82	1.29	i	December 2012– June 2013	5.57	1.36	2.09
10	j	July 2002– November 2002	3.98	0.78	1.22	r	January 2000– September 2000	5.05	1.33	1.97
11	k	May 1992– December 1992	3.02	0.77	1.16	h	January 1987– January 1988	4.75	1.08	1.50
12	l	August 1991– January 1992	3.59	0.72	1.09	d	November 1996– November 1997	4.05	1.00	1.46
13	m	May 2015– November 2015	3.05	0.64	1.02	p	October 2013– April 2014	4.38	0.94	1.44
14	n	June 2007– February 2008	1.58	0.58	0.95	—	May 1986– January 1987	3.96	0.89	1.24
15	o	June 1985– December 1985	1.94	0.57	0.90	f	May 1995– September 1995	2.96	0.77	1.17
16	p	October 2013– May 2014	2.66	0.60	0.85	k	May 1992– December 1992	3.31	0.86	1.17
17	q	April 1997– December 1997	1.61	0.50	0.80	n	June 2007– April 2008	1.66	0.77	1.17
18	r	June 2005– January 2006	1.90	0.52	0.78	j	July 2002– December 2002	3.57	0.78	1.12
19	s	March 1980– August 1980	2.68	0.55	0.77	a	July 1984– December 1984	2.57	0.67	0.99
20	t	July 2003– January 2004	1.89	0.51	0.77	s	January 1980– January 1981	1.72	0.67	0.97

^a The “—” means that the SPEI identified event corresponds to other SPEI-based events instead of the top 20 events listed in the table.

FIG. 4. Comparison of the top 20 drought events. The text and size of each bubble correspond to the “rank-label” and the combined metric in Table 2, respectively.

China and then moves to northern China, reaching its severity peak in January/February 1999.

Drought-g is the 2009–10 drought over southwestern China. It is the most severe drought of the past 50 years, which induced approximately \$30 billion in losses (Yang et al. 2012). Both SPI-g and SPEI-g capture the major drought center over southwestern China. The drought center begins in southwestern China. It lasts several months before breaking into two major subdroughts: one over southwestern China and another short-term drought over Tibet. For these two events, both the SPI and SPEI captured the major characteristics of the droughts, but they differed in detailed spatial locations, areal extent, and severity.

Figure 7 shows the spatial patterns of the average severity for drought-e and drought-g during their major drought periods. Although the SPI and SPEI can well capture the drought centers, the centers delineated by the SPI are more severe than those delineated by the SPEI. By contrast, the SPEI detects larger drought affected areas than those detected by the SPI (see also Figs. 5 and 6).

d. SAD analysis

The SAD envelope curves of the top five drought events (Table 2) are shown in Fig. 8. The drought-averaged severity is negative in the SAD curve, and hence, more (less) negative indicates larger (smaller) severity. The average severity S decreases as the drought area A increases for a given period or duration D . All five SPEI-based events last longer than 12 months, while only three SPI-based events last longer than 12 months. The average severity of the SPI-based events is more severe than that of 5 SPEI-based events over areas within 2 million km^2 and

durations of 1–3 months. For the SPI, within an area of 1–2 million km^2 , the 1983–84 drought, 1998–99 drought, and 2010–11 drought dominate (i.e., largest negative severity) for all durations. For the SPEI, the 1998–99 drought dominates for the duration of 1–6 months, while the 2008–10 drought dominates for the duration of 9–12 months.

Generally, the average severity shows a steep decrease in small areas (0–2 million km^2) for a given drought event, followed by a gradual decrease in larger drought areas (>2 million km^2), for example, the 1983–84 SPI drought event in Fig. 8a-1. This indicates the uneven spatial distribution of drought severity, i.e., more severe in the drought center (~ 1 –2 million km^2) and relatively less severe in the area adjacent to the center (>2 million km^2). The drought temporal evolution shows a similar pattern. Within smaller areas (e.g., 0–2 million km^2), the average severity over a shorter duration (e.g., 1–3 months) is always more severe than that over a longer duration (e.g., >3 months). For example, for the 1983–84 SPI drought, the average severity over 1 million km^2 at $D = 1$ month is more severe than that at $D = 6$ months. Therefore, the uneven temporal evolution of drought severity, with the most severe part often concentrated within a short period, leads to or is followed by relatively less severe periods.

To further assess the drought spatiotemporal dynamics characterized by the SPI and SPEI, the SAD envelope curves of all drought events were reconstructed. For a given duration, within each area interval (increments of $1.5 \times 10^5 \text{ km}^2$ among 0–6 million km^2), we calculate the 50th, 75th, and 100th percentiles of the average drought severity based on the SAD curves of all drought events. The 75th percentile curves with

FIG. 5. Evolution of drought-e over northern China from November 1998 to March 1999. The color bar shows the monthly drought severity (i.e., drought index value).

FIG. 6. Evolution of drought-g over southwestern China from October 2009 to March 2010. The color bar shows the monthly drought severity (i.e., drought index value).

FIG. 7. Average severity (i.e., monthly average of the drought index value) over the drought area during the major periods of drought-e and drought-g.

50th–100th percentile shading bands are shown in Fig. 9. The reason why we focus on the 50th–100th percentile instead of the 0th–50th percentile is because we want to examine the relative severe drought spatiotemporal dynamics.

For short durations ($D \leq 3$ months, Figs. 9a–c), the width of the 50th–100th shading band decreases as the drought area increases. This is because there are a great number of events with small drought areas, which show a high variability of average severity based on these small events. The upper boundaries of the 100th percentiles of the SPI are larger than those of the SPEI, which indicates that the most extreme drought severity detected by the SPI is more severe than that detected by the SPEI.

When $A \leq 1$ million km^2 and $D \leq 2$ months (Figs. 9a,b), the 75th percentile of the average severity for the SPI events is more severe than that for the SPEI events. By contrast, for $D \geq 6$ months and $A \geq 3$ million km^2 (Figs. 9d–f), the 75th percentile of the average severity for the SPEI events is more severe than that for the SPI events. Therefore, the SPI is more likely to identify drought as more severe over small areas ($A \leq 1$ million km^2) and short durations ($D \leq 2$ months), whereas the SPEI tends to delineate drought as more

severe across expansive areas ($A \geq 3$ million km^2) and longer periods ($D \geq 3$ months).

4. Discussion

Within the context of a warming climate, the SPEI characterizes an increase in drought severity, area, and occurrence frequency during 1980–97 compared with those during 1998–2015, while the SPI does not. The increasing PET dominates the significant decrease in the SPEI (i.e., more severe drought); therefore, only considering P in the SPI is not sufficient to detect drought temporal changes within a climate change context. Consistent conclusions were made from previous studies using the SPEI or other drought indices and highlighted the importance of considering PET in drought studies (Chen and Sun 2015; Ayantobo et al. 2017; Shao et al. 2018; Sun et al. 2016, 2017). In addition, Novick et al. (2016) found that elevated PET could directly increase the atmospheric constraints on carbon and water fluxes in many ecosystems. The direct PET effects and its amplified drought impacts imply a concerning future under a continuously warming climate, especially for ecosystems including key national ecological restoration projects (Lu et al. 2018) and agriculture regions

FIG. 8. SAD envelope curves derived from the top five drought events detected by the (a1)–(a6) SPI and (b1)–(b6) SPEI. Note that the y axis is reversed.

(He et al. 2011). These joint impacts are not separately studied here but are worth careful assessments in the future.

PET is co-controlled by multiple meteorological variables, including air temperature (T), wind speed (W_s), relative humidity (R_h), and net radiation (R_n) (Roderick et al. 2007; She et al. 2017). During the most recent 18 years, China experienced a significant increase in T , while the wind speed, relative humidity, and net radiation decreased in most regions (Fig. 10). The decline in net radiation (dimming) and wind speed (stilling) can decrease PET and alleviate meteorological droughts. In comparison, an increase in T (warming)

and a decrease in R_h (drying) can increase PET and intensify meteorological droughts. Zhang et al. (2016) quantified the contributions of meteorological factors to drought using the Palmer drought severity index (Palmer W.C. 1965) in China. They showed that temperature is the dominant factor contributing to drought increase compared to other relieving factors, such as wind speed and radiation. Liu et al. (2011) also found that overall increases in air temperature dominated the increases in panevaporation (linearly correlated with PET) from the early 1990s to 2007. The future climate is believed to experience increasing temperature (Wang and Chen 2014) and potentially increasing PET. Therefore, we

FIG. 9. Reconstructed SAD envelope curves. Solid lines are the 75% percentile of the average severity, and the shading boundaries are the 50th–100th percentiles of the average severity, over durations and area intervals for SPI (red) and SPEI (blue) droughts. Note that the y axis is reversed.

should pay more attention to the impact of the air temperature on drought under climate change.

The three-dimensional drought clustering algorithm is the key for further SAD analysis. Its parameters should be carefully set to accomplish reasonable event identification (Lloyd-Hughes 2012), including the *radii* (R_{lat} , R_{lon}), *spatial coherent area threshold* (θ_S), and *temporal overlap area threshold* (θ_T). Our study identifies 106 SPI and 99 SPEI events with $D \geq 3$ months in mainland China during 1980–2015. These numbers are comparable with the 143 SPI and 176 SPEI droughts identified by Xu et al. (2015), considering their longer study period (i.e., 1961–2012), smaller regions (only humid and transition regions of China) and lower area thresholds (θ_S and θ_T). However, fewer drought events were identified in Wang et al. (2011), with 76 droughts based on soil moisture percentiles during 1961–2006, and in Shao et al. (2018), with 65 droughts based on the self-calibrating Palmer drought severity index during 1980–2015. One important reason for these apparent differences is probably the parameter setting of θ_T . Our study, together with Lloyd-Hughes (2012) and Xu et al. (2015), set θ_T to the same value as used for θ_S . Wang et al. (2011) and Shao et al. (2018) have not explicitly mentioned how their θ_T values were set, and we infer from their results that this value may have been set to a smaller value or zero because drought events in their papers have relatively longer durations. For example, two temporally successive drought clusters, with a substantial percentage of the area being discrete and a tiny percentage of the area

being consistent, will be arbitrarily identified as one drought if θ_T is a small value or zero. Therefore, to avoid year-long events with tenuous spatial connectivity and to focus mostly on temporally coherent droughts (Sheffield et al. 2009; Lloyd-Hughes 2012), both θ_T and θ_S should be carefully set to nonzero reasonable values for specific studies.

5. Conclusions

We elucidate drought characteristics in China from 1980 to 2015 using the SPI and SPEI. This study highlights the importance of the potential evapotranspiration in delineating drought spatiotemporal dynamics and provides a vital reference for the applicability of the SPI and SPEI under climate change.

The SPEI characterizes an increase in drought severity, area, and occurrence frequency, which are mainly induced by increasing PET. By contrast, the SPI does not reveal these phenomena since the precipitation does not exhibit a significant change.

Compared to the SPI, the SPEI identifies a smaller number of total drought events but with larger total drought areas. In addition, the SPEI identifies a greater number of large events but a smaller number of small events than does the SPI in terms of drought duration, drought affected area, volume, and drought combined metric. There is a large difference in the total drought grid number detected by the two indices. Approximately 30% of the SPI-detected drought grids are not identified

FIG. 10. Comparison of the monthly averages between R18y and F18y. (a) Temperature (denoted as T), (b) wind speed (denoted as Ws), (c) relative humidity (denoted as Rh), and (d) net radiation (denoted as Rn). The “Δ”/“▽” denote the grid percentage with increasing/decreasing change, and the stippling indicates the regions with a significant average difference (Student's t test, $p < 0.05$).

as drought by SPEI, and 40% of the SPEI-detected drought grids are not recognized as drought by SPI.

Both indices can roughly capture the top 20 drought events, but events detected by the SPEI are overall more severe than those detected by the SPI. Among these 20 drought events, more events are detected by the SPEI (i.e., 13 events) in the most recent 18-yr span than are detected by the SPI (i.e., 11 events), indicating that the SPEI can better show that large events become more frequent under a warming context. From the SAD analysis, the SPI is more likely to identify drought as more severe over small areas within 1 million km^2 and short durations less than 2 months, whereas the SPEI tends to delineate drought as more severe across expansive areas larger than 3 million km^2 and periods longer than 3 months.

This study suggests that the increasing potential evapotranspiration can amplify drought and hence implies a concerning future given that potential evapotranspiration increases under a warming climate. Therefore, the SPEI is probably more suitable than the SPI to study the temporal change under climate change. Both the SPI and SPEI are suitable

for monitoring major drought events but may show large differences in drought spatiotemporal dynamics.

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