Spatial-temporal characteristics of drought detected from meteorological data with high resolution in Shaanxi Province, China (postprint)

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Abstract

The spatial pattern of meteorological factors cannot be accurately simulated by using observations from meteorological stations (OMS) that are distributed sparsely in complex terrain. It is expected that the spatial-temporal characteristics of drought in regions with complex terrain can be better represented by meteorological data with the high spatial-temporal resolution and accuracy. In this study, Standard Precipitation Evapotranspiration Index (SPEI) calculated with meteorological factors extracted from ITPCAS (China Meteorological Forcing Dataset produced by the Institute of Tibetan Plateau Research, Chinese Academy of Sciences) was applied to identify the spatial-temporal characteristics of drought in Shaanxi Province of China, during the period of 1979–2016. Drought areas detected by SPEI calculated with data from ITPCAS (SPEI-ITPCAS) on the seasonal scale were validated by historical drought records from the Chinese Meteorological Disaster Canon-Shaanxi, and compared with drought areas detected by SPEI calculated with data from OMS (SPEI-OMS). Drought intensity, trend and temporal ranges for mutations of SPEI-ITPCAS were analyzed by using the cumulative drought intensity (CDI) index and the Mann-Kendall test. The results indicated that drought areas detected from SPEI-ITPCAS were closer to the historical drought records than those detected from SPEI-OMS. Severe and exceptional drought events with SPEI-ITPCAS lower than –1.0 occurred most frequently in summer, followed by spring. There was a general drying trend in spring and summer in Shaanxi Province and a significant wetting trend in autumn and winter in northern Shaanxi Province. On seasonal and annual scales, the regional and temporal ranges for mutations of SPEI-ITPCAS were different and most mutations occurred before the year 1990 in most regions of Shaanxi Province. The results reflect the response of different regions of Shaanxi Province to climate change, which will help to manage regional water resources.

Full Text

Preamble

Spatial-temporal Characteristics of Drought Detected from High-Resolution Meteorological Data in Shaanxi Province, China

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Abstract: The spatial pattern of meteorological factors cannot be accurately simulated using observations from meteorological stations (OMS) that are sparsely distributed in complex terrain. It is expected that the spatial-temporal characteristics of drought in regions with complex terrain can be better represented by meteorological data with high spatial-temporal resolution and accuracy. In this study, the Standard Precipitation Evapotranspiration Index (SPEI) calculated with meteorological factors extracted from ITPCAS (China Meteorological Forcing Dataset produced by the Institute of Tibetan Plateau Research, Chinese Academy of Sciences) was applied to identify the spatial-temporal characteristics of drought in Shaanxi Province, China, during the period 1979–2016. Drought areas detected by SPEI calculated with data from ITPCAS (SPEI-ITPCAS) on the seasonal scale were validated by historical drought records from the Chinese Meteorological Disaster Canon-Shaanxi, and compared with drought areas detected by SPEI calculated with data from OMS (SPEI-OMS). Drought intensity, trend, and temporal ranges for mutations of SPEI-ITPCAS were analyzed using the cumulative drought intensity (CDI) index and the Mann-Kendall test. The results indicated that drought areas detected from SPEI-ITPCAS were closer to the historical drought records than those detected from SPEI-OMS. Severe and exceptional drought events with SPEI-ITPCAS lower than -1.0 occurred most frequently in summer, followed by spring. There was a general drying trend in spring and summer in Shaanxi Province and a significant wetting trend in autumn and winter in northern Shaanxi Province. On seasonal and annual scales, the regional and temporal ranges for mutations of SPEI-ITPCAS were different, and most mutations occurred before 1990 in most regions of Shaanxi Province. The results reflect the response of different regions of Shaanxi Province to climate change, which will help manage regional water resources.

Keywords: SPEI; drought areas; meteorological data; cumulative drought intensity; drying trend; wetting trend

1 Introduction

Drought is a damaging and frequent natural disaster (He et al., 2011) that is significantly related to temperature abnormalities and precipitation shortage (Salehnia et al., 2017a). It is sensitive to climate change (Kogan et al., 2013; Jia et al., 2016) and has a significant impact on economic, ecological, and agricultural activities. Research on the spatial-temporal characteristics of drought helps identify the correlation of drought with meteorological, hydrological, and ecological processes (Yu et al., 2015; Yuan et al., 2015), and further evaluate the impact of climate change on human society.

Currently, research on the spatial-temporal characteristics of regional drought faces three main challenges. First, the applicability of drought indices varies greatly due to the specific climatic features of the study area (Qiao et al., 2012; Yang et al., 2017). Second, the accuracy of drought monitoring depends heavily on the accuracy and spatial-temporal resolution of the input data for the drought index (Liu et al., 2016; Wang et al., 2016; Salehnia et al., 2017b). Third, the occurrence and spatial-temporal distribution of drought events identified by drought indices need validation (Liu et al., 2018; Wang et al., 2018). It is imperative to find an appropriate drought index, a reliable validation method, and meteorological data with high spatial-temporal resolution to improve the quality of drought monitoring over specific regions.

Meteorological drought is generally monitored and measured by multifactorial drought indices involving water and energy balance (Vasiliades and Loukas, 2009; Dai, 2011; Paulo et al., 2012; Gobena and Gan, 2013), such as the Palmer Drought Severity Index (PDSI), Self-calibrated PDSI (Sc-PDSI) (Wells et al., 2004), and Standard Precipitation Evapotranspiration Index (SPEI) (Vicente-Serrano et al., 2010a). PDSI requires parameters including soil water holding capacity, groundwater level, and lake/reservoir level (Ma et al., 2015), which are not available in many circumstances. Furthermore, the temporal scale of PDSI is fixed (Vicente-Serrano et al., 2011), although drought is a multi-scale phenomenon (Changnon and Easterling, 1989; Pandey and Ramasastri, 2010). Sc-PDSI is an improved version of PDSI (Wells et al., 2004; Liu et al., 2015), but the temporal scale is still not alterable. In contrast, SPEI combines the sensitivity of PDSI to evaporation changes and the multi-temporal nature of the Standardized Precipitation Index (SPI) (Vicente-Serrano et al., 2010a). Besides, it needs fewer parameters compared with PDSI when the Thornthwaite (Th) method is used to calculate evaporation. Thus, SPEI has been widely used to elaborate the spatial-temporal characteristics of regional drought and to reconstruct the spatial-temporal distribution of drought (Allen et al., 2011; Meza, 2013).

Much research on drought quantification, monitoring, and analysis has been conducted using machine learning models or spatial interpolation methods with meteorological factors extracted from observations from meteorological stations (OMS) (Jiang et al., 2015; Rhee and Im, 2017; Wang et al., 2019; Zhang et al., 2019). However, the spatial interpolation of meteorological factors (e.g., precipitation) brings significant errors due to sparse observations and complex terrain. The accuracy of SPEI forecasting by machine learning models with multisource data needs further theoretical investigation, particularly because SPEI may vary under different climatic conditions (Rhee and Im, 2017). It is more reliable to adopt meteorological datasets with high spatial-temporal resolution to directly quantify drought based on drought indices (Vicente-Serrano et al., 2010b; Hannaford et al., 2011; Wang et al., 2016). Many studies have tested the applicability of various meteorological datasets in drought analysis at multiple scales under different climatic conditions.

For example, Salehnia et al. (2017b) calculated eight drought indices with AgMERRA (Agricultural Model Intercomparison and Improvement Project based on the NASA Modern-Era Retrospective Analysis for Research and Applications) precipitation data and OMS data for drought monitoring. Results showed that the correlation between drought events and the former was higher than that between drought events and the latter. Naumann et al. (2014) investigated five different datasets and three drought indicators with regard to their capability to improve drought monitoring in Africa. They found that the extents of drought areas identified by drought indicators were different. Spinoni et al. (2019) constructed a dataset of meteorological drought events from 1951 to 2016 based on Global Precipitation Climatology Centre (GPCC) and Climatic Research Unit (CRU) time-series datasets with a spatial resolution of 0.5°. It can be concluded that the spatial resolution and accuracy of the gridded meteorological data and a suitable drought index were essential to identify the occurrence, intensity, and spatial extent of drought.

Multiple metrics (e.g., duration, intensity, and area) of drought events were extracted from historical drought records and served as "ground truth" to validate the estimates obtained from drought indices (Spinoni et al., 2019; Wang et al., 2019). Drought detected from data with high spatial resolution and accuracy can be better validated by drought records. In addition, meteorological data with a long temporal range can help depict the trend of drought. The temporal range (1979–2016) and spatial resolution (approximately 10 km$×10km)ofITPCAS(ChinaMeteorologicalForcingDatasetproducedbytheInstituteofTibetanPlateauRes and CMORPH (Climate Prediction Center Morphing Technique) (starting from 1998). Numerous studies have demonstrated the efficiency of ITPCAS in hydrological and meteorological applications across China (Guo and Wang, 2013; Xue et al., 2013; Wang et al., 2018).

In this study, the spatial-temporal characteristics of drought in Shaanxi Province, China, were reconstructed by SPEI and ITPCAS data, and validated by historical drought records. Firstly, the SPEI of all grids with the spatial resolution of 10 km$×$10 km in Shaanxi Province was calculated with the temperature and precipitation data of ITPCAS (termed as SPEI-ITPCAS) from 1979 to 2016. Then, drought areas detected from SPEI-ITPCAS were validated by drought records extracted from the Chinese Meteorological

Disaster Canon-Shaanxi, and compared with those calculated by OMS and ordinary Kriging interpolation (OKI). Finally, drought intensity, trends, and temporal ranges for mutations of SPEI-ITPCAS in Shaanxi Province from 1979 to 2016 were analyzed using the cumulative drought intensity (CDI) index and the Mann-Kendall (MK) test. This study aims to provide more details about the spatial-temporal characteristics of drought in Shaanxi Province, especially in those ungauged areas which were neglected or poorly represented in previous studies (Jiang et al., 2015; Wang et al., 2019; Zhang et al., 2019).

2.1 Study Area

Shaanxi Province is located on the boundary between the western arid zone and the eastern monsoon zone of China (31°42 -39°35 N, 105°29 -111°15 E; Fig. 1 [Figure 1: see original paper]). Meteorological disasters, especially drought, frequently occur with damaging effects on the ecological system and regional economy. Shaanxi Province can be divided into three regions with regard to geography and climate: the northern Loess Plateau with a cold, arid climate; the middle Guanzhong Plain with a mild climate; and the southern Qinba Mountainous region with a warm, wet climate (Liu et al., 2013).

Qinling Mountains run across the middle of Shaanxi Province with significant climate discrepancy between the northern and southern sides of the mountains. The Loess Plateau in the northern part of Shaanxi Province (briefly, northern Shaanxi) has a sub-arid monsoon climate with average annual precipitation varying greatly from 300 to 600 mm. It is prone to both droughts and waterlogging. The Guanzhong Plain in the middle of Shaanxi Province (briefly, Guanzhong) has a warm sub-humid monsoon climate with average annual precipitation between 550 and 700 mm. The Qinba Mountainous region in the southern part of Shaanxi Province (briefly, southern Shaanxi) has a subtropical humid monsoon climate with average annual precipitation between 800 and 1300 mm. Flash floods and geological disasters occur frequently in this southern region. The annual mean temperature of the entire Shaanxi Province is about 13°C, with regional means of 10°C in the north, 13°C in the middle, and 15°C in the south (Wan et al., 2013). For administrative purposes, Shaanxi Province is divided into ten areas of prefecture-level city (APC). Yulin and Yan' an belong to northern Shaanxi; Baoji, Xianyang, Tongchuan, Weinan, and Xi' an belong to Guanzhong; and Shangluo, Ankang, and Hanzhong belong to southern Shaanxi (Fig. 1).

2.2 Data Sources

Temperature and precipitation data (1979–2016) with the horizontal spatial resolution of 0.1° were extracted from ITPCAS. This dataset was merged with meteorological data from the following sources: China Meteorological Administration data, reanalysis dataset of Princeton, Global Land Data Assimilation System (GLDAS) data, and Global Energy and Water Exchanges-Surface Radiation Budget (GEWEX-SRB) radiation data.

The Chinese Meteorological Disaster Canon-Shaanxi briefly summarizes the start-end months or seasons, duration, severity, areas, and financial loss of drought events. However, drought areas were recorded vaguely. For example, the spatial extent was recorded as parts of the APC, or even parts of northern Shaanxi, Guanzhong, and southern Shaanxi. Furthermore, the severity of drought is hard to quantify from these descriptions. Drought events extracted from records of the Chinese Meteorological Disaster Canon-Shaanxi (Zhai, 2005) during the period 1979-2016 are shown in Table 1 . It can be seen that Guanzhong and northern Shaanxi were more frequently affected by drought from 1979 to 2016.

In this study, meteorological observations including precipitation and temperature during the period 1979-2016 were downloaded from the China Meteorological Information Center (http://data.cma.cn/). Because these data were collected under rigorous quality control, no modifications were made for this study.

2.3 Methods

Drought characteristics of Shaanxi Province were analyzed through the following steps in this study. Firstly, SPEI was calculated with OMS at each standard meteorological station of Shaanxi Province and then interpolated into 10 km $\times$ 10 km grids by OKI (termed as SPEI − OMS). Then, SPEI was calculated by temperature and precipitation data extracted from ITPCAS at 10 km $\times$ 10 km grids of Shaanxi Province (termed as SPEI-ITPCAS). Both SPEI-OMS and SPEI-ITPCAS were calculated on seasonal and annual scales, and reclassified into drought and non-drought areas. The drought areas and period of drought occurrence were identified and then validated by comparison with historical records of drought events listed in Table 1. Secondly, spatial distributions of drought intensity, trend, and temporal ranges for mutations of SPEI-ITPCAS in Shaanxi Province during the period 1979–2016 were analyzed on seasonal (SPEI 3) and annual (SPEI 12) scales using the CDI index and the MK test.

2.3.1 SPEI Model SPEI (Vicente-Serrano et al., 2010a) reflects the characteristics of drought or waterlogging by calculating the difference between precipitation and potential evapotranspiration (PET). Currently, PET is generally calculated by the Penman-Monteith (PM) equation (Allen et al., 1994) or Th (Thornthwaite, 1937) parameterization schemes. The PM scheme needs unavailable parameters such as reflectivity of ground objects in each grid of Shaanxi Province, whereas the Th scheme needs only latitude and monthly temperature data (Tsakiris et al., 2007), which are available for this study. Thus, the Th scheme was selected in this study. The calculation of SPEI was described as follows:

Firstly, monthly potential evapotranspiration (PETi) was estimated by the Th scheme using Equation 1:

$$PET_i = 16K\left(\frac{10T_i}{I}\right)^m$$

where PETi (mm) is the potential evapotranspiration of month i; K is a correction coefficient computed as a function of the latitude and month; Ti (°C) is the mean temperature of month i; I is an annual heat index; and m is a polynomial with parameter I.

Secondly, monthly water deficit or surplus Di was calculated by monthly precipitation Pi and PETi:

$$D_i = P_i - PET_i$$

The calculated Di values can be aggregated at different time scales. The water deficit or surplus in a given month i and year j at the time scale of k (k$ $12) months was defined as Equations 3 and 4:

$$D_{i,j}^k = \sum_{l=i-k+1}^{i} D_{l,j}$$

where Dl,j (mm) is the water deficit or surplus in the month l of year j; and Dl,j-1 (mm) is the water deficit or surplus in the month l of year j-1.

According to the Kolmogorov-Smirnov test, the log-logistic distribution was the best to fit SPEI at time scales from 1 to 24 months compared with Pearson III and Gamma distribution (Vicente-Serrano et al., 2010a; Yu et al., 2014). Thus, the log-logistic distribution was used to calculate SPEI after Dk i,j series were normally standardized. The probability distribution function f(x) and cumulative distribution function F(x) of the log-logistic distribution for Dk i,j series were defined in Equations 5 and 6, respectively:

$$f(x) = \frac{\beta}{\alpha}\left(\frac{x-\gamma}{\alpha}\right)^{\beta-1}\left[1+\left(\frac{x-\gamma}{\alpha}\right)^{\beta}\right]^{-2}$$

$$F(x) = \left[1+\left(\frac{x-\gamma}{\alpha}\right)^{\beta}\right]^{-1}$$

where α, β, and γ are the scale, shape, and origin (γ<Di<∞) parameters, respectively.

Finally, SPEI can be calculated by Equations 7 and 8:

$$SPEI = W - \frac{C_0 + C_{1W} + C_{2W}^2}{1 + d_{1W} + d_{2W}^2 + d_{3W}^3}$$

$$W = \sqrt{-2\ln(P)} \quad \text{for } P \leq 0.5$$

$$W = -\sqrt{-2\ln(1-P)} \quad \text{for } P > 0.5$$

where W used in Equations 7 and 8 is the standardized value of F(x). Constants used in Equation 7 are listed as follows: C0=2.515517, C1=0.802853, C2=0.010328, d1=1.432788, d2=0.189269, and d3=0.001308. In Equation 8, if P$ $0.5, then P can be calculated as P=1-F(x), where P is the probability of exceeding the determination of Di; whereas if P>0.5, P can be calculated as P=F(x).

In this study, SPEI was calculated on seasonal (SPEI 3) and annual (SPEI 12) scales. Categories of drought and waterlogging classified by SPEI are shown in Table 2 .

2.3.2 Ordinary Kriging Interpolation (OKI) OKI makes an unbiased estimation of variables at target locations by a weighted linear combination of neighboring observations. It has been widely used as a popular Kriging technique to interpolate meteorological factors. Previous studies showed that OKI outperformed other methods including Inverse Distance Weighted, Thiessen Polygons, and Simple Kriging in precipitation interpolation (Zhang and Srinivasan, 2009; Szcześniak and Piniewski, 2015). Details of using OKI for precipitation interpolation can be found in the original study of Goovaerts (2000).

2.3.3 Cumulative Drought Intensity (CDI) CDI on seasonal and annual scales can integrate the drought severity and frequency of various forms of drought, providing ways to evaluate drought over the long-term period (Kim et al., 2002; Loukas et al., 2008). It can well indicate the cumulative impact of drought on human society in a specific region. We calculated CDI according to the following steps: firstly, we calculated the SPEI-ITPCAS of each grid on seasonal and annual scales; secondly, we accumulated the drought (SPEI-ITPCAS lower than -0.5) according to the temporal range (Kim et al., 2002; Loukas et al., 2008). The larger the absolute cumulative SPEI-ITPCAS is, the greater the CDI is. Drought areas with cumulative SPEI-ITPCAS less than -14.0 were calculated by summing the areas of the grids with high CDI values.

2.3.4 Mann-Kendall (MK) Test MK test (Mann, 1945; Kendall, 1975) was used in this study for trend and trend mutation tests. MK test is widely applied in trend analysis of meteorological and environmental factors, such as precipitation, temperature, and runoff (Ahmad et al., 2015). The principle of MK trend test was described below.

MK trend test assumed that the original time series xt=(x1, x2, ···, xn) was random and independent with no significant trend. The statistical variable S was defined in Equation 9:

$$S=\sum_{i=1}^{n-1}\sum_{j=i+1}^{n}\operatorname{sgn}(x_j-x_i)$$

where sgn is a symbolic function; and xj and xi are the values of variables of the time series. If n$ $10, S can be approximately normally distributed. In addition, variable Z was used to show the results of significance test, which was defined as Equation 10:

$$Z=\begin{cases}\frac{S-1}{\sqrt{\operatorname{var}(S)}} & \text{if } S>0\\ 0 & \text{if } S=0\\ \frac{S+1}{\sqrt{\operatorname{var}(S)}} & \text{if } S<0\end{cases}$$

In a two-sided hypothesis test, positive and negative values of Z corresponded to upward and downward trends, respectively. If |Z|≤Z1-α/2 (α is the significance level), the original hypothesis was accepted, namely, the time series data had no significant trend; otherwise, the hypothesis was rejected, and the time series data had a significant trend. Moreover, if |Z|$ $1.28, 1.64, and 2.32, the significance test was accepted at significance levels of 90%, 95%, and 99%, respectively.

In this study, we conducted the mutation test of MK according to the following descriptions. The MK trend variation test assumed that the original time series xt=(x1, x2, ···, xn) was random and independent with no significant trend. The statistical variable UFk was the forward sequence and was defined as Equation 11:

$$UF_k=\frac{S_k-E(S_k)}{\sqrt{\operatorname{var}(S_k)}}\quad k=1,2,...,n$$

where Sk represents the total numbers of xj which is smaller than xi (j<i) preceding all xi and is defined in Equations 12 and 13:

$$S_k=\sum_{i=1}^{k} r_i$$

$$r_i=\begin{cases}1 & \text{if } x_i<x_j\\ 0 & \text{if } x_i\geq x_j\end{cases}$$

where E(Sk) represents the expectation of Sk; var(Sk) represents the variance of Sk; and k represents the sequence number. Statistical parameter UFk obeys the normal distribution. If |UFk|>Uα/2, the time series data had a significant decreasing or increasing trend. UF k was calculated by the same Equations 11–14 with the reversed time series of xt. When the two curves UFk and UF k intersected between the critical boundary (y=$\pm$Uα), the moment of intersection was when the trend variation begins.

3.1 Validation of SPEI-ITPCAS and SPEI-OMS

Figures 2 and 3 show the drought areas of Shaanxi Province detected from SPEI-ITPCAS and SPEI-OMS, respectively, for years and seasons corresponding to typical drought events. It can be seen that the distribution of drought areas detected from SPEI-ITPCAS and SPEI-OMS were similar in summer of 1991, spring of 1997, autumn of 1998, winter of 1998, and spring of 2001 (Figs. 2 and 3), which accounted for 31.3% of the total seasons. In contrast, there were significant discrepancies of drought areas between the remaining seasons, indicating that meteorological data extracted from OMS and ITPCAS were not spatially consistent with drought monitoring for most of the seasons.

As shown in Table 1, drought occurred in all 10 APCs of Shaanxi Province in nine seasons: springs of 1997 and 2001; summers of 1997 and 1999; autumns of 1995, 1998, and 2010; and winters of 1998 and 2008. In the above nine seasons, the distribution of drought areas identified from SPEI-ITPCAS (Fig. 2 [Figure 2: see original paper]) was consistent with the historical records from the Chinese Meteorological Disaster Canon-Shaanxi (Table 1). In contrast, in summer of 1999 and winter of 2008, drought areas identified from SPEI-OMS (Fig. 3 [Figure 3: see original paper]) were different from the historical drought records from the Chinese Meteorological Disaster Canon-Shaanxi (Table 1), with the absence of north of Guanzhong.

Table 3 lists the discrepancies of drought areas detected from different sources, i.e., historical drought records (Table 1) and SPEI-ITPCAS (Fig. 2), while Table 4 shows the discrepancies of drought areas between historical drought records (Table 1) and SPEI-OMS (Fig. 3). Compared with the seasons and regions in which drought events occurred, the discrepancies of drought areas between the two SPEI results and historical records happened in summer and in north of Guanzhong and northern Shaanxi frequently. Discrepancies of drought areas listed in Table 3 were similar to those in the same season listed in Table 4. However, Table 4 presents more discrepancies than Table 3. Discrepancies of drought areas shown in Table 4 were more likely to occur in Yulin, Tongchuan, and Weinan, which were frequently affected by drought. In conclusion, the detection of drought areas from SPEI-ITPCAS presented higher accuracy than that from SPEI-OMS. Therefore, SPEI-ITPCAS was adopted to analyze the spatial-temporal characteristics of drought in Shaanxi Province.

3.2 Distribution of CDI

Figure 4 [Figure 4: see original paper] shows that the cumulative SPEI-ITPCAS (SPEI-ITPCAS lower than -0.5) in Shaanxi Province from 1979 to 2016 was within -10.0 to -20.0 on seasonal and annual scales. On seasonal and annual scales, the cumulative SPEI-ITPCAS was within -10.0 to -14.0 in most regions of Shaanxi Province. When the cumulative SPEI-ITPCAS was less than -14.0, the region was defined as a typical area with high CDI values. On the winter scale, the cumulative SPEI-ITPCAS was within -16.0 to -20.0 in most regions of Shaanxi Province and the CDI values were higher than those on other seasonal and annual scales.

Figure 4a indicates that areas with higher CDI values in spring were mainly distributed on the eastern and western boundaries of Guanzhong and in southern Shaanxi (A1 and A2), especially in southeast of Guanzhong and northwest of southern Shaanxi (A2) with an area of more than 2000 km^2 and high CDI values on seasonal and annual scales. In summer, areas with high CDI values were mainly distributed in Yulin (B1) and Shangluo (B2; Fig. 4b). In autumn, areas with high CDI values were located in Yan' an (C1) and Hanzhong (C2; Fig. 4c). On an annual scale, the CDI values in western Yulin (E1) and eastern Shangluo and Weinan (E2; Fig. 4e) were high. However, Figure 4d indicates that the CDI values in winter in the whole region were abnormally high, which is not consistent with the historical drought records (Zhai, 2005). Thus, the CDI in winter was not analyzed in this section.

The frequencies of severe and exceptional drought in Shaanxi Province from 1979 to 2016 are shown in Table 5 . The rank of drought frequency on different scales was as follows: summer>spring>annual>autumn; however, the discrepancies between different scales were not significant. From Figure 4 and Table 5 we can conclude that drought occurred most frequently and seriously in summer, followed by spring. Southeast of Guanzhong and northwest of southern Shaanxi were the most sensitive areas to the impact of drought with the highest CDI value and the largest drought area in spring and summer and on an annual scale. In addition, eastern Yulin, southern Yan' an, and Hanzhong were also likely to be affected in summer and autumn.

3.3 MK Test of Precipitation, Temperature, and SPEI-ITPCAS

As shown in Figures 5 and 6, temperature presented a significant increasing trend (Z$ 1.28)*inmostregionsofShaanxiProvinceonseasonalandannualscales.OnlypartofAnkangshowedani* in summer, autumn, and winter. However, the significance and variation trend of precipitation and SPEI-ITPCAS in MK test varied in most regions of Shaanxi Province on the seasonal scale. Tables 6 and 7 show the significance and variation trends of precipitation and SPEI-ITPCAS on seasonal and annual scales in Shaanxi Province, respectively.

In spring, the upward trend of precipitation occurred in most regions of Shaanxi Province, except for parts of Guanzhong. Moreover, the temperature showed a significant upward trend at the 99% confidence level. The SPEI-ITPCAS showed a drying trend in most regions of Shaanxi Province, except for part of southern Shaanxi. The variation trends of SPEI-ITPCAS and precipitation were opposite in most regions, which indicated that the abnormal increase of temperature dominated meteorological processes, leading to a drying trend in most regions.

In summer, the downward trend of precipitation together with the significant upward trend of temperature led to a general drying trend in most regions of Shaanxi Province. This drying trend was especially significant in parts of Yan' an and Guanzhong, and west of southern Shaanxi. Almost all of the five APCs in Guanzhong showed a significant drying trend. The situation was consistent with historical drought records, which indicated that drought in spring and summer was quite serious in Guanzhong and northern Shaanxi (Zhai, 2005).

In autumn and winter, the significant upward trend of precipitation mainly occurred in northern Shaanxi, while the downward trend mainly occurred in Guanzhong and southern Shaanxi. The temperature showed a significant upward trend in all regions. The variation trends of SPEI-ITPCAS reflected a composite interaction of precipitation and temperature with remarkable spatial heterogeneity in Shaanxi Province. In conclusion, we found a significant wetting trend in northern Shaanxi and a significant drying trend in parts of Xi' an, Weinan, Hanzhong, and Ankang.

The variation trends of precipitation and temperature in northern Shaanxi, Guanzhong, and southern Shaanxi on an annual scale were similar to those on autumn and winter scales. The wetting trend in northern Shaanxi was less significant than the upward trend of precipitation, and the drying trends in Guanzhong and southern Shaanxi were more significant than the downward trend of precipitation on an annual scale. The phenomena showed that the significant upward trend of temperature in Shaanxi Province counteracted the upward trend of precipitation (leading to a less significant wetting trend in northern Shaanxi) and interacted with the downward trend of precipitation (leading to a more significant drying trend in Guanzhong and southern Shaanxi).

3.4 Temporal Ranges for Mutations of SPEI-ITPCAS on Seasonal and Annual Scales

As shown in Figure 7 [Figure 7: see original paper], the temporal ranges for mutations of SPEI-ITPCAS can be notably discerned on seasonal and annual scales in Shaanxi Province. For example, mutations of SPEI-ITPCAS occurred during the period 1990-2000 in west of Shaanxi Province and east of Guanzhong in spring (Fig. 7a). In summer, they occurred during the period 1990-2000 in west and middle of Guanzhong (Fig. 7b). In autumn, they appeared after the year 2000 in north of northern Shaanxi (Fig. 7c). In winter, they occurred after the year 2000 in east and middle of Guanzhong and in parts of southern Shaanxi (Fig. 7d). On an annual scale, mutations of SPEI-ITPCAS occurred during the period 1990-2000 in west and middle of Guanzhong, and after the year 2000 in parts of northern Shaanxi (Fig. 7e).

In conclusion, the regional and temporal ranges for mutations of SPEI-ITPCAS differed on seasonal and annual scales, and most mutations happened before the year 1990. As Shaanxi Province has three types of terrain with comparably diverse climates (i.e., cold and arid plateau in the north, mild plain in the middle, and wet and warm mountainous regions in the south), the regional responses to climate change varied. The discrepancies of temporal ranges for mutations of SPEI-ITPCAS indicated that the responses of the three sub-regions (northern Shaanxi, Guanzhong, and southern Shaanxi) to climate change may be quite different.

4.1 Meteorological Data with High Spatial-Temporal Resolution

Validation of SPEI-OMS and SPEI-ITPCAS has proved that meteorological datasets with high spatial-temporal resolution can better reflect the characteristics of drought in regions with complex climate than OMS. Thus, comprehensive evaluations of the existing meteorological datasets in drought monitoring are necessary. Vicente-Serrano et al. (2010b) has proposed a worldwide drought index dataset based on SPEI calculated with 0.5° net CDF reanalysis data. However, it is too coarse for drought monitoring at the provincial scale. ITPCAS, TRMM, and CMORPH-PDF (CMORPH calibrated by probability density function matching and optimal interpolation method) are commonly used for provincial drought analysis in China (Tian and Li, 2015; Lu et al., 2018). ITPCAS has a higher spatial resolution than TRMM and a longer time range than CMORPH. Moreover, numerous studies have shown the superior performance of ITPCAS in predicting precipitation in hydrological simulations in China (Guo and Wang, 2013; He et al., 2015). Kan et al. (2013) pointed out that the accuracy of spatial distribution of precipitation data derived from ITPCAS for western China was better than those of TRMM Multi-satellite Precipitation Analysis (TMPA3B42V6) and CMORPH. In the future, we will downscale ITPCAS with auxiliary environmental factors to finer resolution so that the spatial-temporal characteristics of drought can be identified even more precisely.

4.2 Assessment of SPEI

According to the algorithms of SPEI, the accuracy of SPEI depends on three factors: (1) accuracy of precipitation data; (2) accuracy of calculated PET; and (3) choice of probability density function to fit water deficit or surplus. Precipitation from ITPCAS has been proved to be effective in modeling applications (Wang et al., 2018). Many scholars have verified that the log-logistic function, which is a probability density function used for calculating SPEI, fits well the distribution of water surplus (Beguería et al., 2014; Yang et al., 2016). Therefore, the algorithms used for calculating PET, including PM equation and Th method, need further evaluation. The error of PET calculated by Th method has been shown to be high in winter (Duan et al., 2013; Parsons et al., 2019). Figure 4d showed that in Shaanxi Province, the CDI value on the winter scale was abnormally higher than those on other seasonal and annual scales. This anomaly happened because low temperature in winter caused errors in the calculation of PET by Th method. Thus, estimates of PET in winter calculated by Th method need to be adjusted.

4.3 Adjustments of Th Method in Winter

Figures 2 and 4d and Table 3 showed that drought areas in winter detected by SPEI-ITPCAS were relatively consistent with the historical drought records, while the CDI in winter was abnormal, indicating that Th method tended to overestimate the intensity of drought in winter. Tsakiris et al. (2007) proposed that the ratio of precipitation to potential evapotranspiration (briefly, P/PET) can be used as an appropriate drought index and as a way to distinguish arid and humid regions (Paulo et al., 2012). Because arid and humid regions are relatively stable, PET calculated by Th method in winter can be adjusted by P/PET values.

5 Conclusions

In this study, temperature and precipitation data were extracted from ITPCAS to calculate SPEI, and the calculation results were then validated by historical drought records. Spatial-temporal characteristics of drought on seasonal and annual scales in Shaanxi Province during the period 1979–2016 were analyzed by SPEI-ITPCAS. Results showed that SPEI-ITPCAS was superior to SPEI-OMS in detecting drought areas of Shaanxi Province on seasonal and annual scales. The rank of drought frequency on different scales was as follows: summer>spring>annual>autumn. The CDI values in Shaanxi Province during the period 1979–2016 were different on seasonal and annual scales. In spring and summer, there was a general drying trend in most regions of Shaanxi Province while a significant drying trend occurred in Weinan and Xi' an. In autumn and winter, there was a significant wetting trend in northern Shaanxi while a drying trend occurred in other regions. Mutations of SPEI-ITPCAS occurred before the year 1990 in most regions of Shaanxi Province on different time scales.

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