A Multi-Scale Daily SPEI Dataset for Drought characterizing at Observation Stations over the Mainland China from 1961 to 2018

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Highlights:

- A multi-scale daily SPEI dataset was developed across the mainland China from 1961 to 2018.
- The daily SPEI dataset can be used to identify the start and end day of the drought event.
- The developed daily SPEI dataset in this study is free, open and persistent publicly available.

Abstract:

The monthly Standardized Precipitation Evapotranspiration Index (SPEI) can be used to monitor and assess drought characteristics with one month or longer drought duration. Based on data from 1961 to 2018 at 427 meteorological stations across the mainland China, we developed a daily SPEI dataset to overcome the shortcoming of coarse temporal scale of monthly SPEI. Our dataset not only can be used to identify the start and end dates of drought events, but also can be used to investigate the meteorological, agricultural, hydrological and socioeconomic droughts with different time scales. In the present study, the SPEI data with 3-month (about 90 days) scale were taken as a demonstration example to analyze spatial distribution and temporal changes in drought conditions for the mainland China. The SPEI data with 3-month (about 90 days) scale showed no obvious intensifying trends in terms of severity, duration, and frequency of drought events from 1961 to 2018. Our drought dataset serves as a unique resource with daily resolution to a variety of research communities including meteorology, geography, and natural hazard studies. The daily SPEI dataset developed is free, open and persistent publicly available from this study. The dataset with daily SPEI is publicly available via the figshare portal (Wang et al, 2020c), with https://doi.org/10.6084/m9.figshare.12568280.

Key words:

SPEI, mainland China, drought, spatial-temporal, Multi-scale, meteorological data

1. Introduction

Drought is one of the most destructive natural hazards worldwide. It can lead to adverse effects to the ecological system, industrial production, agricultural practices, drinking water availability, hydrological processes and water quality (Bussi and Whitehead, 2020; Lai et al., 2019; Vicente-Serrano et al., 2012; Wang et al., 2014; Wang et al., 2017). Drought has brought about ca. 221 billion dollars loss during 1960 to 2016 reported by the International Disaster Database (EM-DAT), and the drought events in South Asia have influenced over 60 million residents from 1998 to 2001 (Agrawala et al., 2001). Unfortunately, the drought is expected to increase in frequency and intensity due to the future warming air temperature (Trenberth et al., 2014; Zambrano et al., 2018). The exacerbated drought conditions have promoted some national legislation (such as drought preparedness and plan) to carry out the risk management and adaptive strategy for drought disasters (Garrick et al., 2017).

The various drought types result in the difficulty of drought characterizing and assessment. Drought definition is not unique. Some proposed defining drought according to the water deficit (Wilhite and Glantz, 1985), while others defined drought based on the period of abnormal arid conditions (Eslamian et al., 2017). The popular drought can be classified into four types including (1) meteorological, (2) agricultural, (3) hydrological, and (4) socioeconomic droughts (Mishra and Singh, 2010). The meteorological drought results from precipitation deficit or evaporation increases (McKee et al., 1993). The meteorological drought can propagate into the agricultural drought with the lower soil moisture availability, and it also can lead to hydrological drought with lower streamflow and socioeconomic drought with lower water availability (Barella-Ortiz and Quintana-Seguí, 2019; Gevaert et al., 2018). In general, drought indices are normally used to monitor and assess the condition or spatial-temporal characteristic of drought.

Many drought indices have been developed for the drought characterizing and assessment, such as the Palmer drought severity index (PDSI) (Dai et al., 2004), standardized precipitation index (SPI) (McKee et al., 1993), vegetation water supply index (VWSI) (Carlson et al., 1994), vegetation health index (VHI) (Kogan, 2002), vegetation temperature condition index (VTCI) (Wan et al., 2004), and other drought indices (Men-xin and Hou-quan, 2016; Wang et al., 2015; Wang et al., 2017). PDSI and SPI are the most popular drought studies worldwide (Dai et al., 2004; McKee et al., 1993), however, they have some limitations. PDSI is only suitable to the agricultural drought through characterizing the soil water deficit, and it cannot identify the meteorological, hydrological, and socioeconomic droughts (Feng and Su, 2019). In addition, PDSI limits the spatial comparability of drought due to the fact that it is heavily depending on data calibration (Sheffield et al., 2009; Yu et al., 2014). Although the SPI can be used to monitor and assess different drought types by multiple spatial scales at the monthly time step, it only considers the precipitation factor and neglects effects of evaporation stemmed from temperature and other meteorological factors (Wang et al., 2014; Wang et al., 2017; Yang et al., 2018). To solve the above problems, the Standardized Precipitation Evapotranspiration Index (SPEI), which considers the advantage of both PDSI and SPI, was developed to monitor and assess droughts (Vicente-Serrano et al., 2010). It not only accounts for the effect of evaporation on drought, but also have the capability of spatial comparability and characterizing different drought types with multiple time scales (Feng and Su, 2019; Wang et al., 2015). SPEI can be used to delineate spatial-temporal evolution of drought, drought characteristics, and impacts of drought at the regional and global scales (Mallya et al., 2016; Wang et al., 2014).

However, the commonly used SPEI fails to identify droughts with less than one-month duration (Van der Schrier et al., 2011; Vicente-Serrano et al., 2010). With the future climate change, flash droughts have been recently categorized as a type of extreme climate events. Flash droughts occur along with sudden onset, rapid aggravation, and sudden end of drought could lead to severe consequences (Pendergrass et al., 2020). It is imperative for characterizing the flash droughts with the short-term duration (e.g., several days). To use the sub-month resolution drought index, we have developed the daily SPEI for the first time, and our daily SPEI has been used to assess the drought and its impacts in previous studies (Wang et al., 2015; Wang et al., 2017). The new SPEI can not only identify the drought with one-month and more than one-month duration, but also monitor the drought with several days duration. In addition, our new daily SPEI has filled the gap in the capability to monitor the onset and duration of droughts. Our daily SPEI has similar principles with the commonly used month SPEI in terms of time accumulation effects (Vicente-Serrano et al., 2010; Wang et al., 2015; Yu et al., 2014). The daily SPEI data with different time scales can also meet the requirement of characterizing and assessing of different drought types (meteorological drought, agricultural drought and hydrological drought) at multi-time scales (Wang et al., 2014).

The SPEI can be calculated by the difference between daily precipitation and daily potential evapotranspiration (PET) (Vicente-Serrano et al., 2012). Precipitation general can be directly obtained by the meteorological observation stations (Wang et al., 2015). But PET can be only estimate by driver of meteorological data or remote sensing data (Wang et al., 2018; Wang et al., 2017). Although there are at least 50 methods to calculate the PET potential evapotranspiration, the methods estimate the inconsistent and different values due to diverse assumptions, data inputs and climatic regions (Grismer et al., 2002; Lu et al., 2005). PET plays an important role in understanding fluxes of the heat and mass of atmospheric system at the local and global scale (Thomas, 2000). Thus, it is necessary to choose the suitable method to estimate PET. The choice of candidate probability distributions for SPEI calculation is also very important (Vicente-Serrano et al., 2010; Vicente-Serrano et al., 2012), the chosen distribution for SPEI generally need a location parameter because climatic water balance may have the negative values (when PET> precipitation in certain a periods) (Wang et al., 2015; Wang et al., 2017). Distributions for SPEI normalization have generalized logistic distribution, Pearson Type III distribution, normal distribution, generalized extreme value (GEV) distribution (Stagge et al., 2015). The four candidate SPEI distributions have the best good-ness of fitting the accumulated climatic water balance (Stagge et al., 2015; Wang et al., 2015; Wang et al., 2017). However, The GEV distribution has the best performance among all four probability distributions across the whole Continental Europe, because of the lower rejection frequencies of GEV by using several tests (Kolmogorov–Smirnov (K–S), Anderson–Darling (A–D), and Shapiro–Wilk (S–W)) (Stagge et al., 2015), therefore, we choose the GEV distribution fitting he accumulated climatic water balance to calculate SPEI. The SPEI are suited to investigate the effect of climate change and global warming on drought severity. SPEI has been widely used in diverse studies on drought variability and impact, and drought monitoring systems (Boroneant et al., 2011; Fuchs et al., 2012; Potop et al., 2014; Sohn et al., 2013).

The aim of this study, therefore, is to produce a long record (1961-2018) daily drought index dataset for the whole mainland China. Specifically, we used the new daily SPEI algorithm to produce the multi-time scale drought dataset at a daily time resolution. Meteorological data with 427 stations including multi-factor (daily precipitation, daily average air temperature, daily minimum air temperature, daily maximum air temperature and sunshine) are used. The developed drought dataset at the national scale has the potential to be used to monitor and assess droughts and their impacts for the sectors including agricultural sector, forest sector, hydrological sector, ecological sector, environmental sector and so on.

2. Data Sources and Methods

2.1 Data Sources

Daily meteorological data from 1960 to 2018 were collected from the National Meteorological Science Data Sharing Service Platform (http://data.cma.cn/). The data, which have gone through quality controlling, have been used in many studies on drought (Li et al., 2019; Wang et al., 2019). In total, there are 839 stations with public data. To ensure continuous and complete data records, 427 meteorological stations are chose for our study by removing stations with missing data exceeding 30 days over the whole period. Meteorological variables include the minimum and maximum air temperature (°C), precipitation (mm) and sunshine duration (h). The sunshine duration was converted to solar radiation based on the Ångström function (Chen et al., 2010; Wang et al., 2015). The station location is shown in Figure 1.

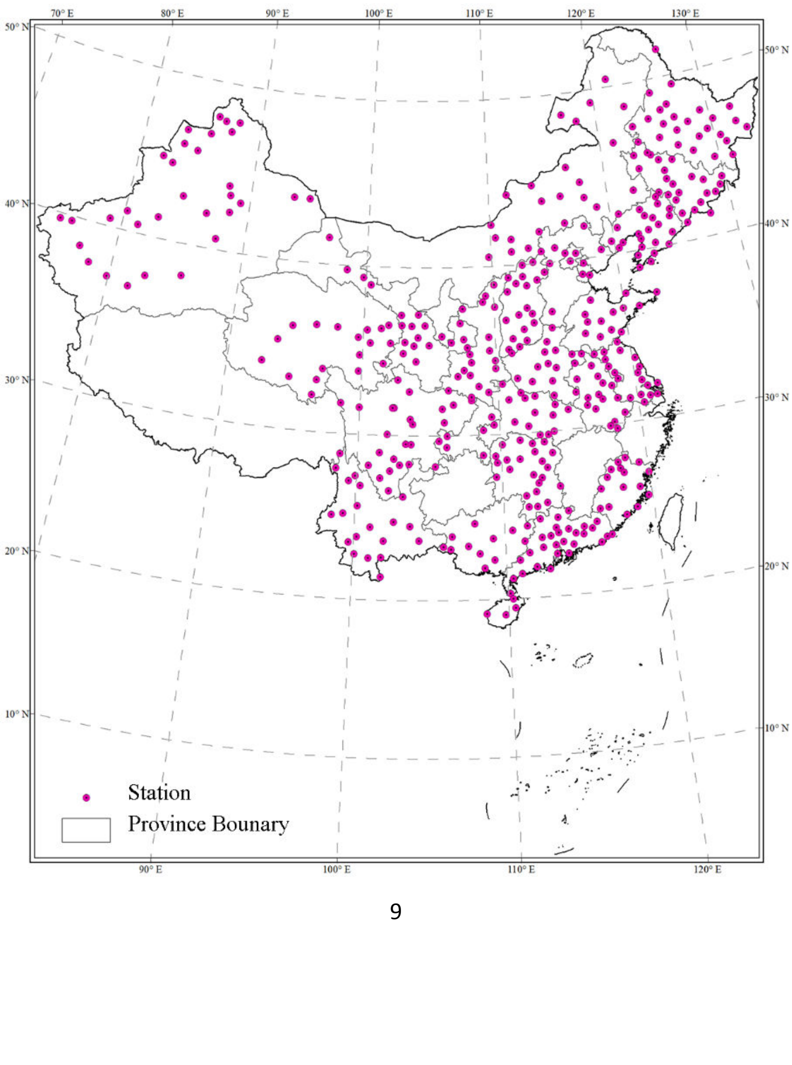

Figure 1. The location of meteorological stations across the mainland China.

2.2 Daily SPEI Calculation

The daily SPEI can be calculated by the difference between daily precipitation and daily potential evapotranspiration. Because air temperature and solar radiation explained at least 80% of evapotranspiration variability (Martí et al., 2015; Priestley and Taylor, 1972), the Hargreaves model based on temperature and solar radiation can be used to estimate the daily potential evapotranspiration (Hargreaves and Samani, 1982; Mendicino and Senatore, 2013; Wang et al., 2015). The daily potential evapotranspiration can be obtained by the following formula:

$$PET = 0.0023 * (T_{mean} + 17.8) * \sqrt{(T_{\max} - T_{\min})} * R_a \quad (1)$$

where, T_{mean} is the daily average air temperature (^{o}C); $T_{\max}$ and $T_{\min}$ are the daily maximum and minimum air temperatures (^{o}C), respectively; and R_a is the daily net radiation on the land surface (MJ m^{-2} d^{-1}).

SPEI calculation depends on the accumulating deficit or surplus (D_i) of water balance at different time scales. D_i can be determined based on precipitations (P) and PET formula given day i:

$$D_i = P_i - PET_i \quad (2)$$

The obtained D_i values are summed at different time scales, following the same procedure as that for the commonly used SPEI. The $D_{i,j}^{k}$ in a given day j and year i depends on the chosen time scale k (days). For example, the accumulated difference for 1 day in a particular year i with a 30-day (or other time scales) time scale is calculated using:

$$X_{i,j}^{k} = \sum_{l=31-k+j}^{30} D_{i-1,l} + \sum_{l=1}^{j} D_{i,l} \quad , \qquad \text{if } j < k \text{ and}$$
$$X_{i,j}^{k} = \sum_{l=j-k+1}^{j} D_{i,l} \quad , \qquad \text{if } j \geq k \tag{3}$$

We also need to normalize the water balance into a probability distribution to get the SPEI index series. The best distribution for SPEI calculation is the generalized extreme value (GEV) distribution (Stagge et al., 2015), which can overcome the limitation of original SPEI through generalized logistic distribution for short accumulation (1–2 months) periods (Stagge et al., 2015; Vicente-Serrano et al., 2010). Therefore, we adopted the GEV distribution to standardize the D series into SPEI data series (Monish and Rehana, 2020). The GEV probability density function is:

$$f(x)=\begin{cases} \left(\dfrac{1}{\sigma}\right)\left[\left(1+\xi z(x)\right)^{-1/\xi}\right]^{\xi+1} e^{-\left[\left(1+\xi z(x)\right)^{-1/\xi}\right]}, & \xi \neq 0,\ 1+\xi z(x)>0 \\ \left(\dfrac{1}{\sigma}\right) e^{-z(x)-e^{--z(x)}}, & \xi \neq 0,\ -\infty<x<\infty \end{cases} \tag{4}$$

where,

$$z(x) = \frac{x-\mu}{\sigma} \tag{5}$$

where, ξ, σ, and μ are the shape, scale, and location parameters respectively. The cumulative distribution function $F(x)$ of GEV can be calculated by the following equation:

$$F(x)=e^{-(t(x))} \tag{6}$$

where,

$$t(x)=\begin{cases}\left(1+\xi\left(\frac{(x-\mu)}{\sigma}\right)\right)^{\frac{-1}{\xi}}, & \text{if}\xi\neq 0\\ e^{-(x-\mu)/\sigma}, & \text{if}\xi=0\end{cases} \tag{7}$$

Thus, the probability distribution function of the D series is given by:

$$F(x)=[1+(\frac{\alpha}{\chi-\gamma})^{\beta}]^{-1} \tag{8}$$

With $F(x)$, the SPEI can easily be obtained as the standardized values of $F(x)$. Following the classical approximation of Abramowitz and Stegun (1965):

$$SPEI=W-\frac{C_0+C_1W+C_2W^2}{1+d_1W+d_2W^2+d_3W^3} \tag{9}$$

where, $W=\sqrt{-2\ln(P)}$ for $P\leq 0.5$ and P is the probability of exceeding a determined D value, P=1-$F(x)$. If $P>0.5$, then P is replaced by 1-P and the sign of the resultant SPEI is reversed. The constants are C_0= 2.515517, C_1=0.802853, C_2=0.010328, d_1= 1.432788, d_2=0.189269, and d_3=0.001308.

2.3 Drought Analysis Method

The daily SPEI dataset were calculated in five accumulating periods (30 days, 90 days, 180 days months, 360 days, 720 days) based on the water balance (difference between precipitation and PET). The classifications for the SPEI drought classes are presented in Table 1.

Table 1 Categorization of drought and wet grade according to the SPEI(Wang et al., 2014).

Categorization	SPEI values
Extremely Wet	SPEI≥ 2
Severe Wet	1.5 ≤SPEI< 2
Moderate Wet	1 ≤SPEI< 1.5

Mild Wet	0.5 <SPEI< 1
Normal	-0.5 ≤SPEI≤ 0.5
Mild Drought	-1 <SPEI< -0.5
Moderate Drought	-1.5 <SPEI≤ -1
Severe Drought	-2 <SPEI≤ -1.5
Extremely Drought	SPEI≤ -2

We used the method described by Yevjevich (1967) to define the drought characteristics (severity, duration, and intensity). A drought event can be firstly determined by drought start and end dates, and its duration and severity were then assigned. Thus, we accounted for the continuity of drought propagation. The continuous days with SPEI values less than the threshold (such as -0.5,-1.0,-1.5,-2) are defined as the duration of a drought event. The severity is the integral area between absolute value of the SPEI with value <-0.5 and the horizontal axis (SPEI = 0) from the drought start day to the drought end day. The drought frequency is the total number of drought events in a period. The drought event and its characteristics (severity, duration, and intensity) can be demonstrated in Figure 2.

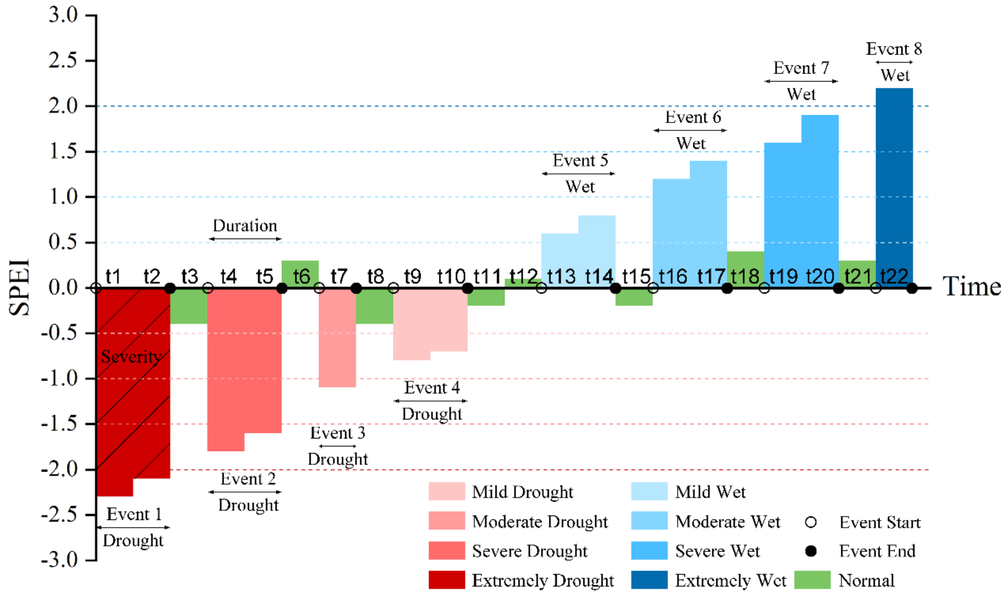

Figure 2. Schematic diagram of drought and wet events (the red shaded area denotes the drought events; the blue shaded area denotes the wet events).

The SPEI data based on 90-day (3-month) time scales can be used to identify soil moisture or agriculture droughts (Wang et al., 2014). Due to its important applications, we selected the SPEI data with the 90-day time scales as the example data for analyzing in the present study. To investigate the spatial-temporal characteristics of the example data, we defined three variables including Annual Total Drought Severity (ATDS), Annual Total Drought Duration (ATDD), and Annual Total Drought Frequency (ATDF). The three variables were obtained by summing the severity, duration, and frequency of all the drought events in each year at 427 stations.

We also used the non-parametric Mann–Kendall (MK) test to detect monotonic trends (Kendall, 1948; Mann, 1945), because MK test does not require data normality (Mann, 1945; Wang et al., 2020a; Wang et al., 2020b). We computed slopes for ATDS, ATDD and ADF using the Sen's method (Sen, 1968). These statistical methods are commonly used in analyses of water resources, climate, and ecology data. For the MK test, the global trend for the entire series is significant when P-value < 0.05.

3 Analysis Results

3.1 Spatial Distribution of Drought Characteristics

The ATDS can be used to identify hot spots with more severe drought conditions. Figure 3 shows the calculated ATDS values across the mainland China. We categorized ATDS values into two main groups with higher ATDS values indicated more severe drought conditions. The distribution of ATDS values shows that, in general, northeastern parts of China had more severe drought conditions than southern parts. However, our results also indicate that the humid climate zone in the south also experienced severe drought conditions, though not as much as for northern parts of China (Figure 3).

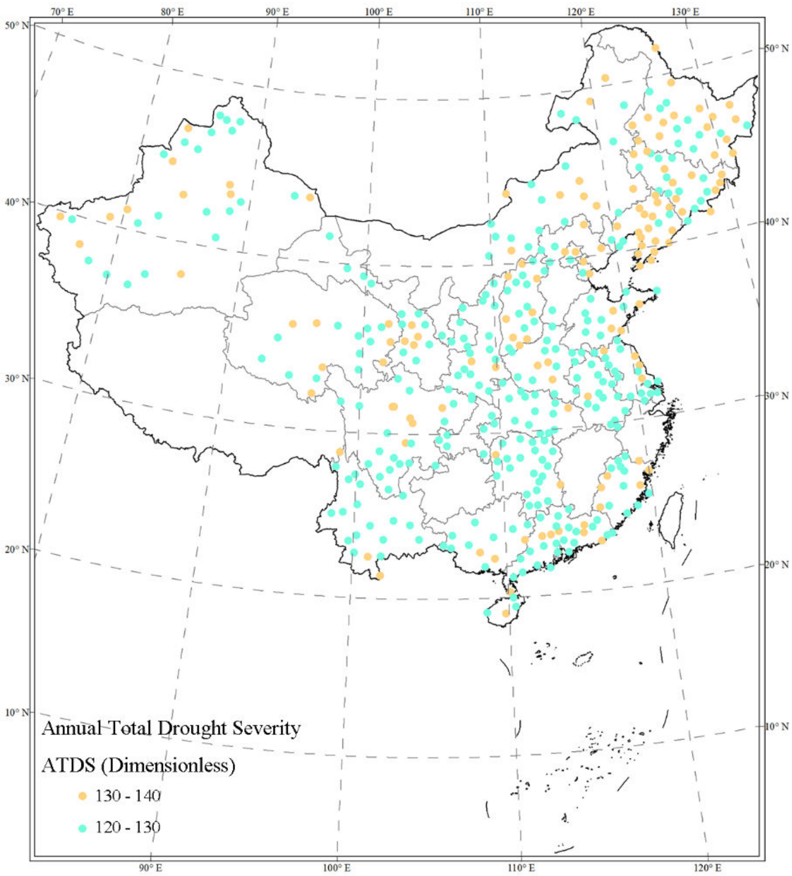

Figure 3. The spatial distribution of ATDS across the mainland China.

Figure 4 shows that ATDD values ranged from 100 to 110 days for most stations across the mainland China. This indicates that there was near one-third of a year when most stations were experiencing drought conditions. More stations with ATDD values ranging from 100 to 110 were found compared with stations with ATDD values of 120-130 (Fig. 4). For drought years, the duration days of drought events are expected to be were longer. The ATDD had similar spatial distribution characteristics with the ATDS, indicating that droughts also occurred in the humid climate zone.

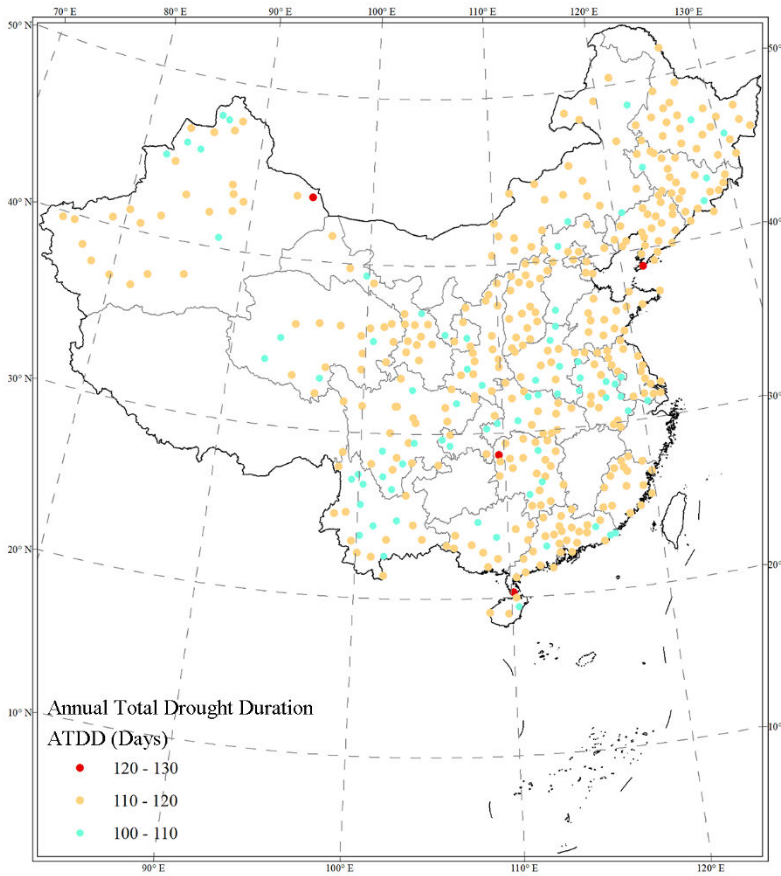

Figure 4. The spatial distribution of ATDD across the mainland China.

Figure 5 shows the spatial distribution of ATDF values across the mainland China. In general, most stations had 4-6 annual drought events. There were fewer stations with 6-8 annual drought events compared with stations with 2-4 annual drought events. We also detected that drought events could be occurring in both arid and humid regions based on spatial distributions of ATDF values (Figure 5). Since the ATDF indicated only the annual average drought events, we could expect that for the severer drought years the ATDF would have greater values for different stations.

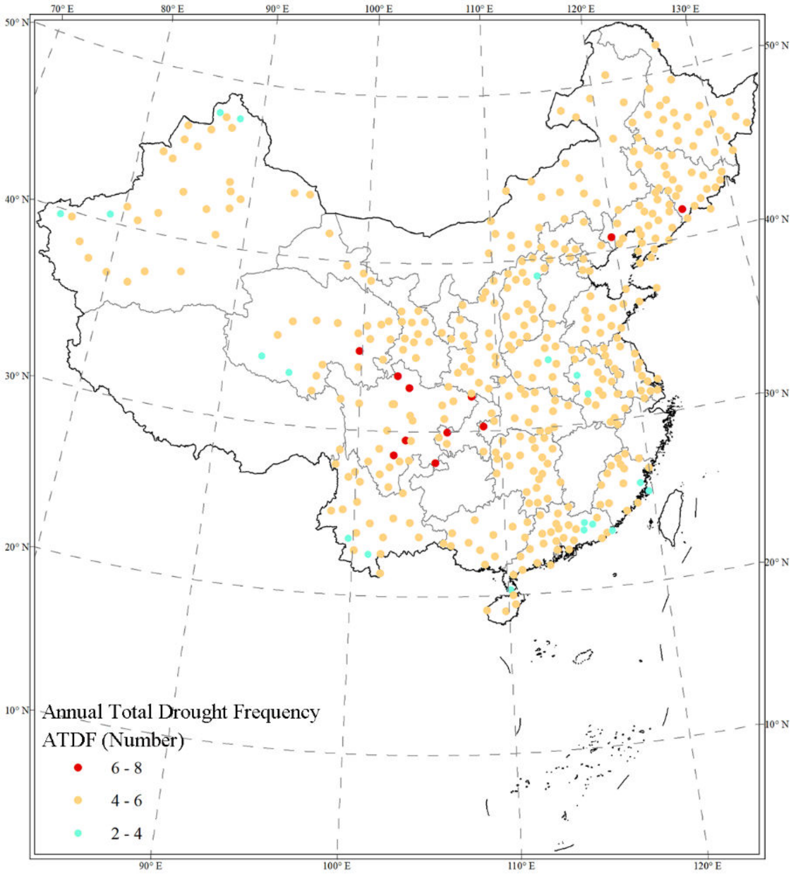

Figure 5. The spatial distribution of ATDF across the mainland China.

3.2 Trends in Drought Characteristics

The changing trends of ATDS can be used to detect whether drought severity is weakening or intensifying with time, Figure 6 shows that the spatial distribution of changing trends of ATDS from 1961 to 2018 across the mainland China. In general, there were more stations with weakening trends in drought severity than those with intensifying trends across all stations (Figure 6). It seems that both weakening and intensifying absolute values were largest in the northeast, northwest, and central China compared with other parts. However, after scrutiny, we found that drought severity tended to weaken in the northeast, northwest, and center China with more stations having significant weakening tends by statistical test (P-value<0.05; Figure 6). For southern China, most stations had no significant trends in either weakening or intensifying of drought severity (P-value>0.05; Figure 6).

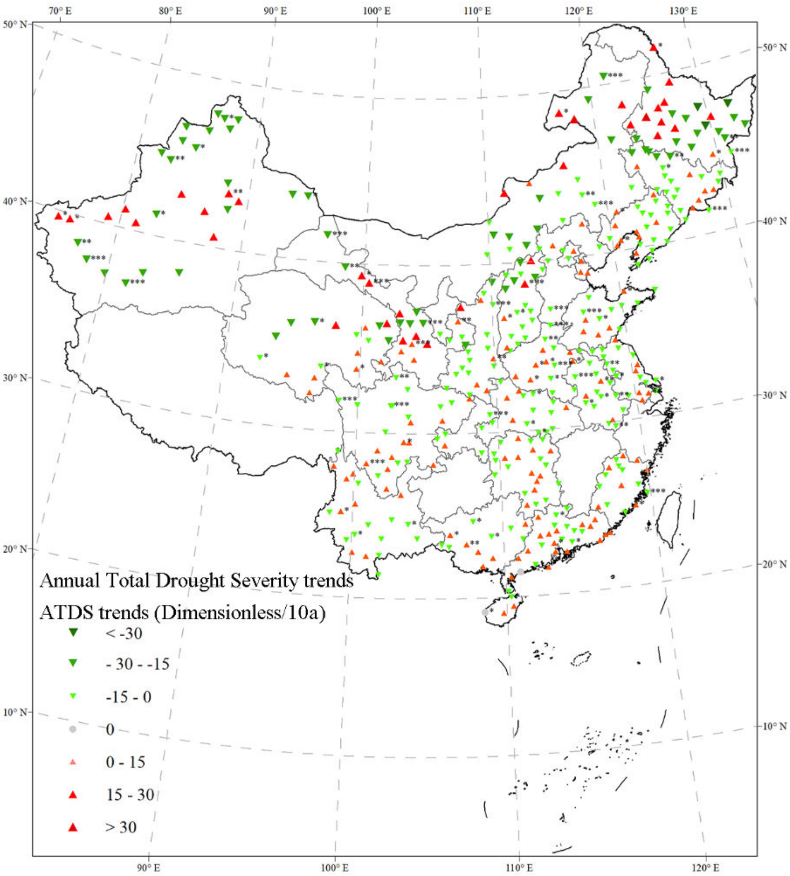

Figure 6. The spatial distribution of the changing trends of ATDS (the red and green triangular indicate increasing and decreasing trends, respectively. "***" denotes P-value < 0.001, "**" denotes P-value <0.01, and "*" denotes P-value < 0.05).

The changing trends of ATDD can be used to detect whether drought duration is getting shorter or longer. Figure 7 shows the spatial distribution of changing trends for the ATDD across all stations. In general, stations in the southeast demonstrated downward trends with shortening drought duration, while stations in the northwest had upward trends for the ATDD with increasing drought duration (Figure 7). Note that the increasing or decreasing trends for ATDD were significant (P value < 0.05) for stations across the central China indicating that the central China regions were suffering dramatic changes of drought conditions.

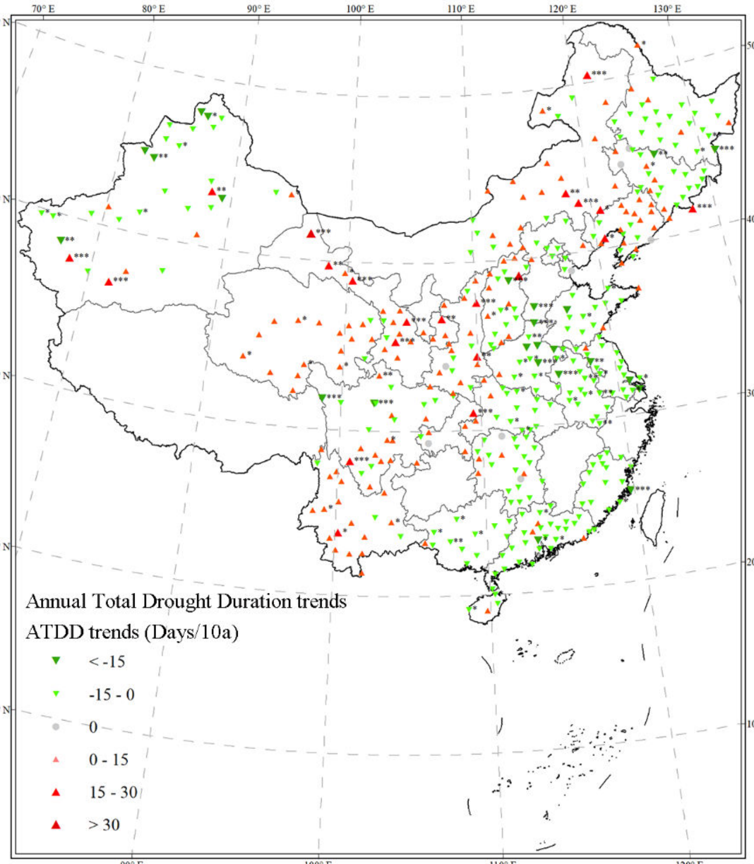

Figure 7. The spatial distribution of the changing trends of ATDD (the red and green triangular indicate increasing and decreasing trends, respectively. "***" denotes P-value < 0.001, "**" denotes P-value <0.01, and "*" denotes P-value < 0.05).

The changing trends of ATDF can be used to detect whether the frequency of drought events is increasing or decreasing with time. Figure 8 shows the spatial distribution of changing trends of ATDF across all stations. Most stations demonstrated no significant trend in the frequency of drought events, except for dozens of stations in western China having significant upward trends (P-value < 0.05) with increasing frequency in drought events, and stations in northeastern China demonstrated significant downward trends (P-value < 0.05) with decreasing frequency of drought events.

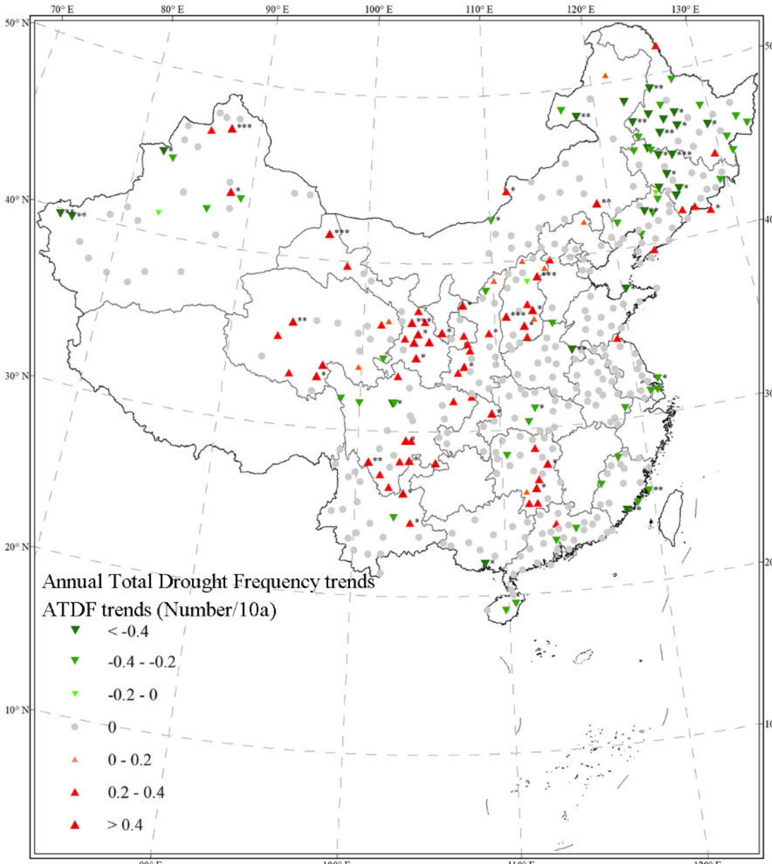

Figure 8. The spatial distribution of the changing trends of ATDF (the red and green triangular indicate increasing and decreasing trends, respectively. "***" denotes P-value < 0.001, "**" denotes P-value <0.01, and "*" denotes P-value < 0.05).

4. Discussion

The reason for selecting 90 days (3-month) scale to assess spatial and temporal characteristics of drought conditions across the mainland China is because the SPEI with the 90 days (3-month) scale can indicate the agricultural drought (or soil moisture) (Van der Schrier et al., 2011; Wang et al., 2014; Wang et al., 2017), and its results are comparable with the PDSI (Dai et al., 2004; Van der Schrier et al., 2011) and other drought indices including Surface Water Supply Index (SWSI) and Moisture Adequacy Index (MAI) (Doesken and Garen, 1991; McGUIRE and Palmer, 1957). The commonly used monthly SPEI have been used to assess drought characteristics and their impacts worldwide from the regional scale to the global scale (Stagge et al., 2015; Vicente-Serrano et al., 2010; Wang et al., 2014). The SPEI with different time scales is relevant for meteorological drought (1-month timescale), agricultural drought (3-6-month timescale about 90-180 days), hydrological drought (12-month timescale about 360 days), and socioeconomic drought (24-month timescale about 720 days), respectively (Homdee et al., 2016; Potop et al., 2014; Tirivarombo et al., 2018; Vicente-Serrano et al., 2010).

Our new SPEI dataset with multi-time scales were developed and compiled using the daily SPEI algorithm in the previous study (Wang et al., 2015). The daily SPEI has been used in drought characterizing and assessment, and was validated by drought characterizing and assessment (Jevšenak, 2019; Jia et al., 2018; Salvador et al., 2019; Wang et al., 2015; Wang et al., 2017). The global SPEI database with monthly temporal resolution and 0.5 degree spatial resolution is available (https://spei.csic.es/database.html). The database covers the period between January 1901 and December 2018. Although the database can be used effectively for the meteorological, agricultural, hydrological, and socioeconomic droughts, it cannot identify and detect the flash drought with less than one-month duration. In addition, the monthly database can only detect the start month and end month of drought events, and therefore it fails to determine the start and end dates of a drought event, (Kassaye et al., 2020; Vicente-Serrano et al., 2010; Wang et al., 2014). Our newly developed daily SPEI can compensate the shortcomings of monthly SPEI in drought characterizing and assessment. In addition, we used the well-received GEV probability distribution for the SPEI calculation for our dataset (Stagge et al., 2015).

Although the daily SPEI has better performance in drought characterizing and assessment (Jevšenak, 2019; Wang et al., 2017), the uncertainty of daily SPEI still needs to be evaluated in future works. Our daily SPEI dataset used the simple Hargreaves model based on temperature and solar radiation to estimate daily potential evapotranspiration (Hargreaves and Samani, 1982; Wang et al., 2017). We will further investigate effects of various evapotranspiration models (such as CRAE model, Penman algorithm, Thornthwait algorithm, Makkink algorithm, and Priestley–Taylor algorithm) on the calculation of SPEI (Makkink, 1957; Morton, 1983; Penman, 1948; Priestley and Taylor, 1972; Thornthwaite, 1944). We only chose SPEI based on the 90 days (3-month timescale) as an example to analyze drought characteristics, and the results demonstrated that there was no obvious intensifying trends for drought across the mainland China which is consistent with other studies (Han et al., 2020). Meanwhile, our newly developed daily SPEI will be further validated in other regions of the world. In addition, SPEI values at different time scales can be used as a proxy for other type of droughts but it lacks the complete picture (no soil moisture condition, streamflow, etc.) (Zargar et al., 2011).

Our long-term daily SPEI dataset has contributed significantly to our understanding of drought evolution, especially flash drought. The dataset can be used to monitor and assess different drought types (meteorological drought, agricultural drought, and hydrological drought) through different timescale data. It also can identify the start and end dates for drought. The dataset is valuable to meteorological research and natural hazards communities for various purposes such as assessment of extreme climate or drought effect evaluation.

5. Data Availability

All daily SPEI dataset including data and their description at 427 observed meteorological stations, the data is also provided as open access via figshare (Wang et al, 2020c), available at doi.org/10.6084/m9.figshare.12568280. This depository includes the five files directory of the daily SPEI data with five scales (30 days about 1 month, 90 days about 3 month, 180 days months about 6 month, 360 days about 12 month, 720 days about 24 month) and station information for 427 meteorological stations.

6. Summary

In the present study, we have produced a daily SPEI dataset from 1960 to 2018 at 427 meteorological stations across the mainland China. Our open-access dataset is an important contribution to drought assessment, and it can overcome the disadvantages of the commonly used monthly SPEI database. Our daily dataset can help monitor and assess the spatial and temporal characteristics of droughts. It can be used to assess the impacts of droughts on ecological system, hydrological processes, and other natural resources. Our multi-time scale daily SPEI dataset can be widely used in studies on meteorological drought (1-month timescale), agricultural drought (3-6-month timescale), hydrological drought (360 days timescale), and socioeconomic drought (24-month timescale). The dataset will reduce the time spent on research and avoid the duplication of efforts, which will be highly attractive to meteorological, geographical, natural hazard researchers and searchers from other areas.

Author contributions. QFW led the study, developed the method, and wrote the manuscript with input from all the authors. JYQ and XSZ discussed the results and revised the manuscript. All the authors contributed to the final manuscript. QFW, JYZ, RRZ, XPW, and XZZ collected and analysed data over time, providing statistics and material (graphs and tables) for the paper.

Competing interests. The authors declare that they have no conflict of interest.

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