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Daily standardized precipitation index with multiple time scale for monitoring water deficit across the mainland China from 1961 to 2018

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Highlights:

- Developed a new multi-scale daily SPI suitable for different drought types.
- The drought events monitored by the new daily SPI are basically consistent with historical records.
- The characteristics of drought events in mainland China do not increase significantly.
- The multi-scale daily SPI data set is freely available to the public.

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Abstract:

With the increasing shortage of water resources, drought has become one of the hot issues in the world. The standardized precipitation index (SPI) is one of the widely used drought assessment indicators because of its simple and effective calculation method, but it can only assess drought events more than one month. We developed a new multi-scale daily SPI dataset to make up for the shortcomings of the commonly used SPI and meet the needs of drought types at different time scales. Taking three typical stations in Henan, Yunnan and Fujian Province as examples, the drought events identified by SPI with different scales were consistent with the historical drought events recorded. Meanwhile, we took the 3-month scale SPI of soil and agricultural drought as an example, and analyzed the characteristics of drought events in 484 stations in Chinese mainland. The results showed that most of the drought events the mainland China did not increase significantly, and some parts of the northwestern Xinjiang and Northeast China showed signs of gradual relief. In short, our daily SPI data set is freely available to the public on the website https://doi.org/10.6084/m9.figshare.14135144, and can effectively capture drought events of different scales. It can also meet the needs of drought research in different fields such as meteorology, hydrology, agriculture, social economy, etc.

Keyword: Drought, Water Deficit, SPI, China, dataset

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1. Introduction

Drought is the most frequent, complex, chronic, and severe natural disasters worldwide (Wang et al., 2014; Wang et al., 2015; Zhong et al., 2019). Drought areas caused by water deficit have significantly spread in the past several decades over China because of climate change (Chang et al., 2016), drought situation in China will exacerbate in the future decades (Chen and Sun, 2017), the northwestern China is suffer to severe water resources crises and drought risk (Yao et al., 2018). Drought can lead to the adverse effects on drinking water, water resources availability, agricultural production and yield, and ecological environment and ecosystems stability (Passioura, 2007; Heim Jr, 2002; Ledger et al., 2011). drought is also one of the most significant stress factors that greatly result in reduction of agricultural production and crop yield, further causes food security issues and even starvation (Farooq et al., 2016). Drought have induced the severe economic impacts (Wang et al., 2014; Wang et al., 2015), annual approximately 221 billion dollars loss are caused by the drought worldwide from 1960 to 2016 according to statistics of the International Disaster Database (EM-DAT), and drought in China brought in direct economic losses of about USD 10 billion annually between 2004 and 2013 (Hao et al., 2020). Drought monitoring and evaluation have become the hot topics of discussion and attracted the attention from hydrologists, ecologist, geographer, meteorologists, and other the non-scientists (Todisco et al., 2013; Osorio and Galiano, 2012), there are evidences that drought are intensifying in this century in spatial and temporal terms under climate change (Solomon et al., 2007). it lacks to assess the evolution and spatial-temporal characteristics of drought resulting from water anomalies at the country scale (Wang et al., 2015; Wang et al., 2014). Therefore, it is imperative to evaluate and monitor and assess the drought characteristics using the long time series data at the large scale, this can play the important role in water resources management, responses to alleviating drought and drought risks management.

Drought definition is diversified, a common definition of drought is the water deficiency and shortage of precipitation in certain a period (Kim et al., 2018), however, American Meteorological Society (AMS) considers the different drought definition, and divides droughts into four main categories including meteorological drought, agricultural (soil moisture) drought, hydrological drought, and socioeconomic drought (Ams, 1997; Malakiya and Suryanarayana, 2016). Drought indices are developed as the effective tools to monitor and evaluate the spatial-temporal characteristics of different type drought (Ding and Peng, 2020; Wang et al., 2015), because the indices can facilitate communication between water deficit (or anomalies) and numerous stakeholders (or user audiences) (Abeysingha and Rajapaksha, 2020). In the past, the three most popular and representative drought indices are the standardized precipitation index (SPI) (Mckee et al., 1993), the Palmer drought-severity index (PDSI) (Palmer, 1965), and the standardized precipitation evapotranspiration index (SPEI) (Vicente-Serrano et al., 2010b). The other widely used indices include the surface water supply index (SWSI) (Valipour, 2013), the evaporative demand drought index (EDDI) (Hobbins et al., 2016), the Vegetation Condition Index (VCI) (Kogan, 1990), the temperature condition index (TCI) (Kogan, 1995), the vegetation TCI (VTCI) (Wang

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et al., 2001), the crop moisture index (CMI) (Palmer, 1968), the standardized streamflow index (SSI) (Vicente-Serrano et al., 2012), and the Standardized Soil Moisture Index (SSMI) (Hao and Aghakouchak, 2013). Theses drought indices are calculated by the hydrometeorological variables or remote sensing data (Zhiña et al., 2019), the indices except of SPI and SPEI lack multi-time scale characteristics for monitoring the different type drought (Vicente-Serrano et al., 2010b). Although SPEI considers the water balance (the difference between precipitation and evapotranspiration) with the multi-time scale (Wang et al., 2015), its calculation requires the reference evapotranspiration parameter of the research areas or stations, the results of SPEI varied because of the different method in calculating reference evapotranspiration with the same input data (Beguería et al., 2014; Vicente-Serrano et al., 2010b). SPI has the advantage of the simplicity of calculation procedure and flexibility of the different time scale (Mckee et al., 1993), it has been adopted by the World Meteorological Organization as global tool to monitor characteristics since 2009 in the 'Lincoln declaration on drought indices' (Hayes et al., 2011; Mckee et al., 1993). Thus, SPI is effective tool and index to monitor the different kinds of drought and to enable early drought warnings.

The value of SPI standardized the deviation from the mean of precipitation, and can allow to compare the dry (water deficit) or wet (water surplus) condition (Mckee et al., 1993). SPI not only has simplicity of calculation and spatial comparability in humid and arid zones (Guttman, 1998; Vicente-Serrano et al., 2010b), but also has the capability to obtain and recur the drought events detected by other indices (Maccioni et

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al., 2015; Khan et al., 2018). The 1-month scale SPI can be suitable to detect the meteorological drought for the short accumulation of water balance (Mckee et al., 1993), The SPI with 3(or 6)-month scale can indicate the soil moisture conditions or agricultural drought in medium term (Khan et al., 2018; Achour et al., 2020), The 12-month scale SPI can be used to characterize the long-term hydrological drought (Khan et al., 2018), The longer time scale SPI can be employed to analyze the socioeconomic drought (Vicente-Serrano et al., 2010b). The temporal versatility of SPI is very helpful and convenient to identify the onset and cessation of drought event (Tadesse et al., 2018), the robustness and better performance of SPI by comparing the other drought indices have been reported in the previous studies (Guttman, 1998; Mpelasoka et al., 2008; Degefu and Bewket, 2017). Although SPI has been widely accepted and successfully used to monitor and evaluate the characteristics and risk management of the different drought type (Achour et al., 2020; Vicente-Serrano et al., 2012; Viste et al., 2013; Yu et al., 2014), it is generally calculated or obtained though using the monthly precipitation. The monthly SPI only can detect the month of onset and termination of drought (Hayes et al., 2011; Beguería et al., 2014), it cannot identify the onset and termination days of drought events. It is imperative to develop SPI to daily resolution for detailed monitoring and assessing the characteristics of drought especially flash drought.

Our primary aim is to produce and provide a daily drought index dataset with long time series (1961-2018) at the observation meteorological stations over the mainland China, the dataset can be used to monitor and evaluate the different kind of drought

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characteristics. Firstly, we obtain the multi-time scale drought dataset from 1961 to 2018 with temporal resolution of the day using the new daily SPI algorithm based on precipitation at the 484 stations; Secondly, we take the 3-month scale SPI data the example to analyze the spatial-temporal characteristics of drought; Thirdly, we further investigate drought evolution of drought using multi-time scales (1-month scale, 3-month scale, 6-month scale, 9-month scale and 12-month scale) SPI at the typical stations; At last, we describe our dataset format and sharing information to enables users to easily download and use them. Our dataset is anticipated to monitor and assess characteristics and impacts of drought to cope with climate change, our daily SPI data can also be used to evaluate the impact of drought on ecosystem, crop growth growth, crop yield, vegetation phenology and plant activity.

2. Data Sources and Methods

2.1 Data Sources

We used the daily precipitation data of 484 meteorological stations in mainland China from 1961 to 2018 provided by the China Meteorological Data Sharing Service Platform to calculate the SPI dataset (http://data.cma.cn/). These data have undergone strict quality control on the platform and have been widely used in the calculation of various drought indices and drought assessments (Li et al., 2019). The platform provides free meteorological data of 839 meteorological stations in mainland China. In order to ensure the continuity and completeness of data records, we selected precipitation data from 484 stations for calculation and analysis. The distribution of

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these 484 stations is shown in Fig 1.

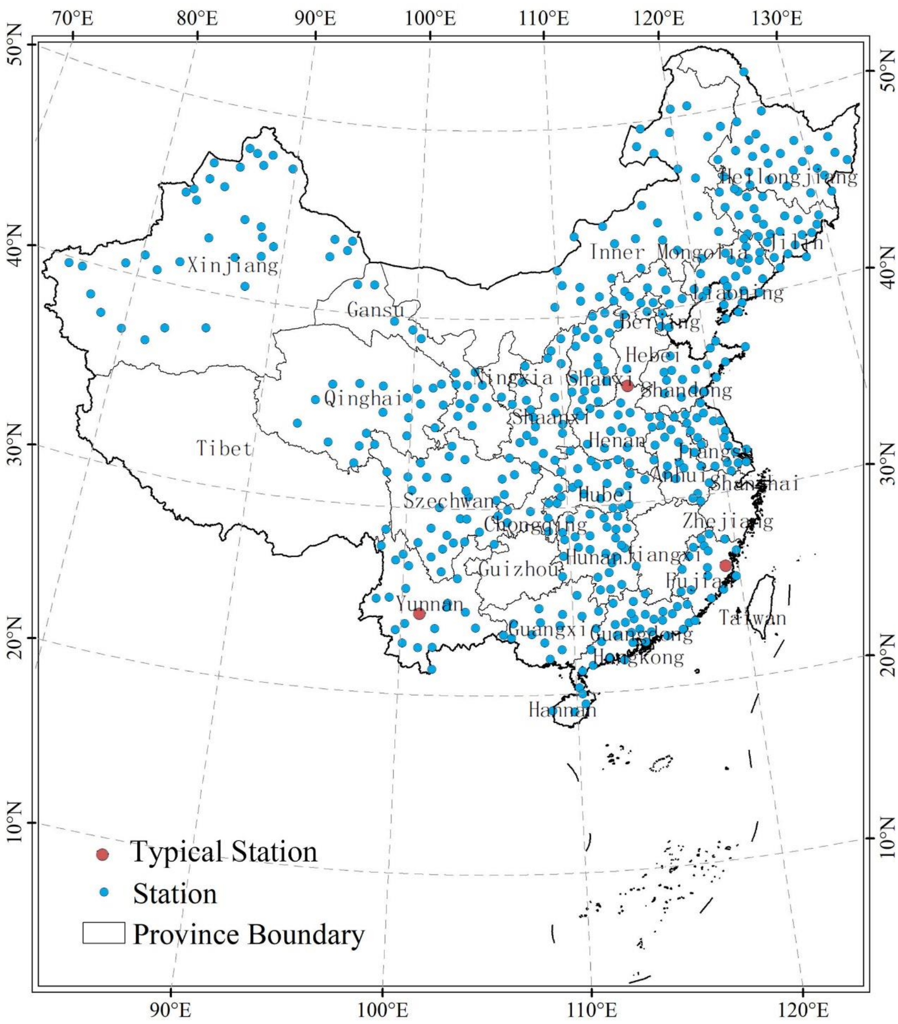

Figure 1. The distribution of meteorological stations across the mainland China, including three typical stations (station 53898 in the Henan, station 56856 in Yunnan, and station 58847 in Fujian).

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2.2 Daily SPI Calculation

The daily SPI can be obtained by fitting and normalizing precipitation data with different probability distribution functions. Many studies have explored the effects of different probability distribution functions on SPI calculation (Sienz et al., 2012; SoˇLáková et al., 2013). The commonly used probability distribution functions for calculating SPI are the gamma distribution Weibull distribution, Gumbel distribution and so on. Among them, the gamma distribution is the best distribution in SPI calculation for its relatively flexible shape parameter (Stagge et al., 2015). Before calculating the probability distribution, we need to obtain the cumulative precipitation series of different time scales. In this study, we used the following functions to construct the daily precipitation series at different time scales (30 days as an example):

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

$$X_{i,j}^{k} = \sum_{l=j-k+1}^{j} P_{i,l} \quad , \qquad \text{if } j \geq k$$

Where, the $X_{i,j}^{k}$ is the cumulative precipitation in a given day j and year i at time scale k (days). $P_{i,l}$ is daily precipitation in day j and year i.

Then, we introduced gamma probability distribution function to calculate the probability distribution of accumulated precipitation series. The probability density function is as follow:

$$f(x) = \frac{1}{\beta^{\gamma}\Gamma(\gamma)} x^{\gamma-1} e^{-\frac{x}{\beta}}, \quad x > 0$$

$$\Gamma(\gamma) = \int_{0}^{\infty} x^{\gamma-1} e^{-x} dx$$

Where, the random variable x is the cumulative precipitation series in a certain time

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scale. $\beta > 0$ and $\gamma > 0$ are scale and shape parameters respectively, which can be calculated by the maximum likelihood estimation method as follow:

$$\hat{\gamma} = \frac{1 + \sqrt{1 + \frac{4}{3}A}}{4A}$$

$$\hat{\beta} = \frac{\bar{x}}{\hat{\gamma}}$$

$$A = \lg\bar{x} - \frac{1}{n}\sum_{i=1}^{n} \lg x_i$$

Where, x_i is the cumulative precipitation series in a certain time scale. n refers to the number of the precipitation series sample. $\bar{x}$ refers to the average of the precipitation series sample.

Suppose the precipitation x_0 at a certain time scale, the probability that the random variable x is less than x_0 is:

$$P(x < x_0) = \int_0^{x_0} f(x)dx$$

Since the domain of the gamma function does not include the case of $x = 0$, while the actual precipitation may be 0, the piecewise probability distribution is then:

$$P(x) = \begin{cases} P_0 + (1 - P_0)F(x) & x > 0 \\ \dfrac{m+1}{2(n+1)} & x = 0 \end{cases}$$

Where, P_0 refers to the historical ratio of periods with zero precipitation. $F(x)$ is the probability distribution for samples with detectable accumulated precipitation. n and m represent the number of samples and the number of samples where total precipitation equals zero.

Next, the gamma probability distribution is normalized:

$$P(x < x_0) = \frac{1}{\sqrt{2\pi}}\int_0^{x_0} e^{-\frac{z^2}{2}}dx$$

Finally, we can get the SPI value:

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$$SPI = z = S\frac{c_0 + W - c_1 W - c_2 W^2}{1 + d_1 W + d_2 W^2 + d_3 W^3}$$

$$W = \sqrt{\ln\frac{1}{P^2}} \quad \begin{cases} P = 1 - F(x) \ , \ S = -1 & F(x) \leq 0.5 \\ P = 1 - P \ , \ S = 1 & F(x) > 0.5 \end{cases}$$

Where, 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.

Based on the commonly used monthly SPI, we developed daily SPI in different time scales (1-month, 3-months, 6-months, 9-months and 12-months) by the method described above. Referring to the classification standard of meteorological drought in China, SPI is divided into 9 categories as shown in Table 1.

Table 1 Drought classification of different grades based on SPI.

Categorization	**SPI values**
Extremely Wet	SPI≥ 2
Severe Wet	1.5 ≤SPI< 2
Moderate Wet	1 ≤SPI< 1.5
Mild Wet	0.5 <SPI< 1
Normal	-0.5 ≤SPI≤ 0.5
Mild Drought	-1 <SPI< -0.5
Moderate Drought	-1.5 <SPI≤ -1
Severe Drought	-2 <SPI≤ -1.5
Extremely Drought	SPI≤ -2

2.3 Theory of Runs

Based on SPI index and run theory, drought characteristics were analyzed. A run in run theory is an unbroken sequence of similar events in a given ordered sequence of two or more types of symbols (Wu et al., 2021). A drought event generally has four drought characteristics: duration, severity, intensity, and frequency (Ashrafi et al., 2020). The determination method of similar events is whether SPI is within the same specified

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threshold. Drought duration refers to the duration of a certain level of drought event from the beginning to the end. Drought severity refers to the sum of SPI during drought events. Drought intensity is the average value of SPI in a certain level of drought event, and equal to the drought severity divided by the drought duration. The total number of drought events in a certain period is defined as drought frequency. Fig. 2 shows the definition and relationship between drought events and their attribute characteristics.

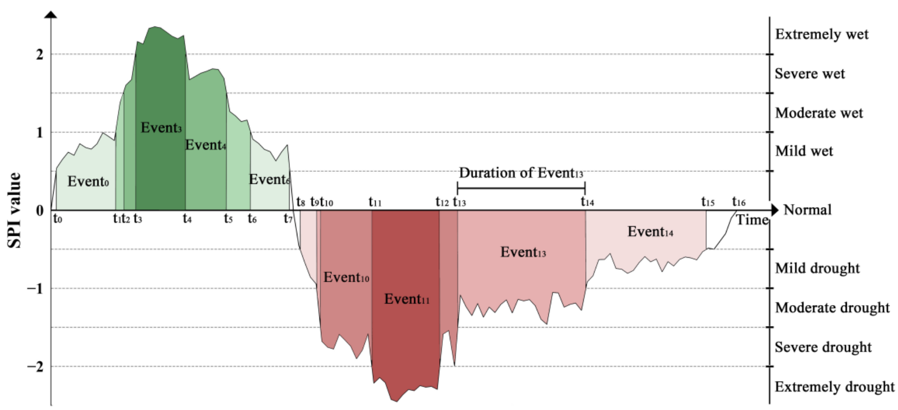

Figure 2. Schematic diagram of drought levels. Different colors represent different levels of drought and wet events.

In addition, we used three typical stations as examples to analyze the characteristics of drought events in different regions. As shown in Fig 1, the three typical regional sites include site 53898 in the Henan, site 56856 in Yunnan, and site 58847 in Fujian. In order to better compare and analyze the characteristics of drought events at China, we took the 3-month scale as an example to calculate the annual total drought intensity (ATDS), annual total drought duration (ATDD), and annual total drought frequency (ATDF) of all sites (Wang et al., 2021b).

2.4 Statistical methods

We used the Theil-Sen (TS) method to estimate the long-term trend of the ATDS, ATDD, and ATDF in all stations. The TS estimator selects the median of the slopes of all straight lines for two-dimensional sample points to estimate the trend (Theil, 1992; Sen and Kumar, 1968). It is proven to be a robust method for monitoring trends in time series and not strongly affected by abnormal values (Ren et al., 2020). Then, the Mann‑Kendall (MK) method was used to test the significance of the long-term trend of the ATDS, ATDD, and ATDF in all stations. As a nonparametric test method, MK does not require the data to obey normal distribution (Mann, 1945; Kendall, 1948). The TS estimator and MK method have been widely used in many fields, such as water environment, ecological remote sensing, climate change and so on. (Zhai et al., 2020; Cai et al., 2020).

3. Results

3.1 Analysis of drought characteristics of typical stations

Fig 3-5 shows the SPI time series curves at the station 53898 (Henan), 58847 (Fujian), 56856 (Yunnan) from 1962 to 2018 at different time scales. In general, the shorter the time scale, the more sensitive the SPI is to short-term precipitation, and the greater the range of SPI value changes. Periodic changes in the SPI value can be observed in the curve of a shorter time scale. The peaks of the curve are mostly concentrated during the rainy season from April to September each year.

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Fig 3 shows that the station 53898 (Henan) experienced severe drought disasters in 1965, 1966, 1978, 1986, 1992, and 1993, which is basically consistent with the drought disaster events recorded in *the Henan Volume of the Chinese Meteorological Dictionary*. According to records, the drought disasters that occurred in Henan Province from 1965 to 1966 were extremely serious, causing rivers and wells to dry up. The precipitation in the northern part of Henan where the station 53898 was located was reduced by more than 60% compared with the normal annual precipitation. Similarly, in Figure 3, we can also find that the station 53898 showed extreme drought from 1965 to 1966, and the SPI value once reached an abnormal value of -3.

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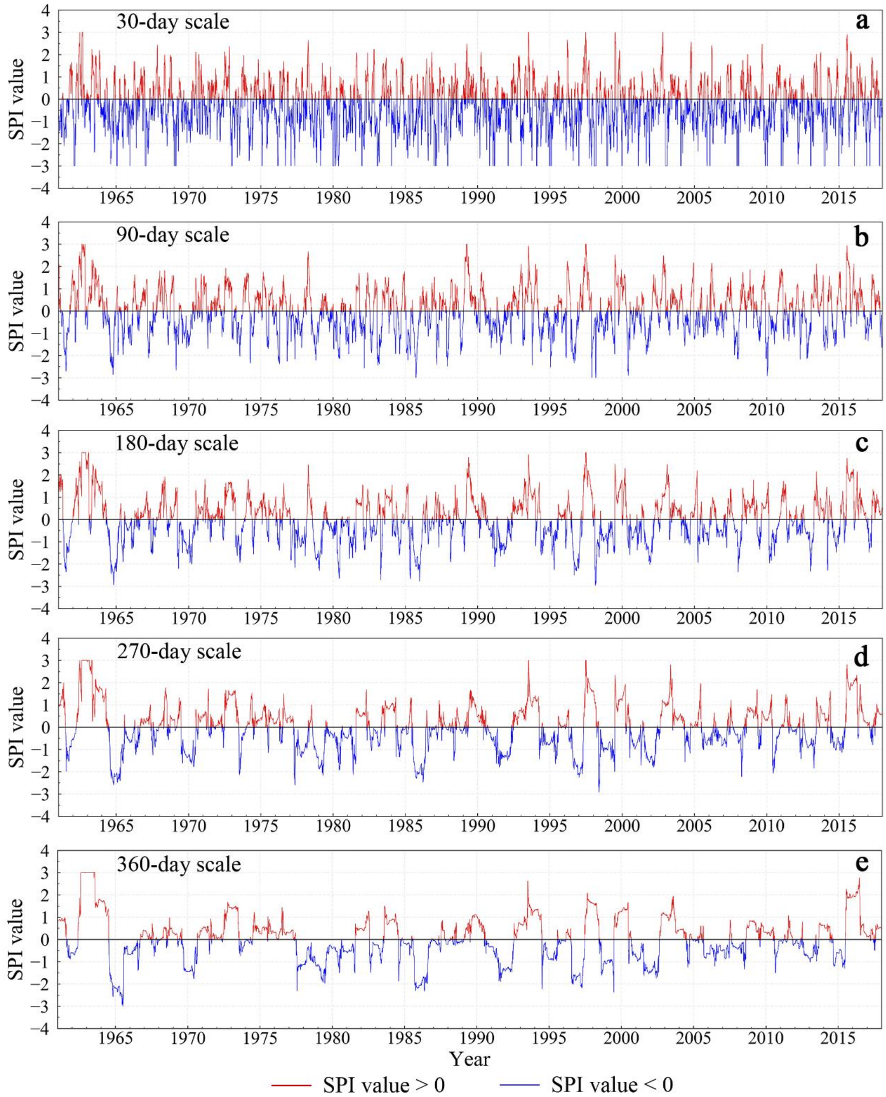

Figure 3. SPI curves of different time scales at station 53898 (Henan) from 1962 to 2018.

According to *the Yunnan Volume of the Chinese Dictionary of Meteorological Disasters*, the years of severe drought in Yunnan from 1949 to 2000 include 1963, 1987, 1988, 1992, and 1998, where Fig 4 shows the trough of the SPI curve. In addition,

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unlike the station 53898, extreme drought events at the station 56856 mostly occurred after 2000. According to *the China Meteorological Disaster Yearbook* from 2004 to 2018, Yunnan Province experienced severe droughts from 2003 to 2004 and from 2009 to 2013. Similarly, the multi-scale daily SPI in Fig 4 also monitored the same drought event.

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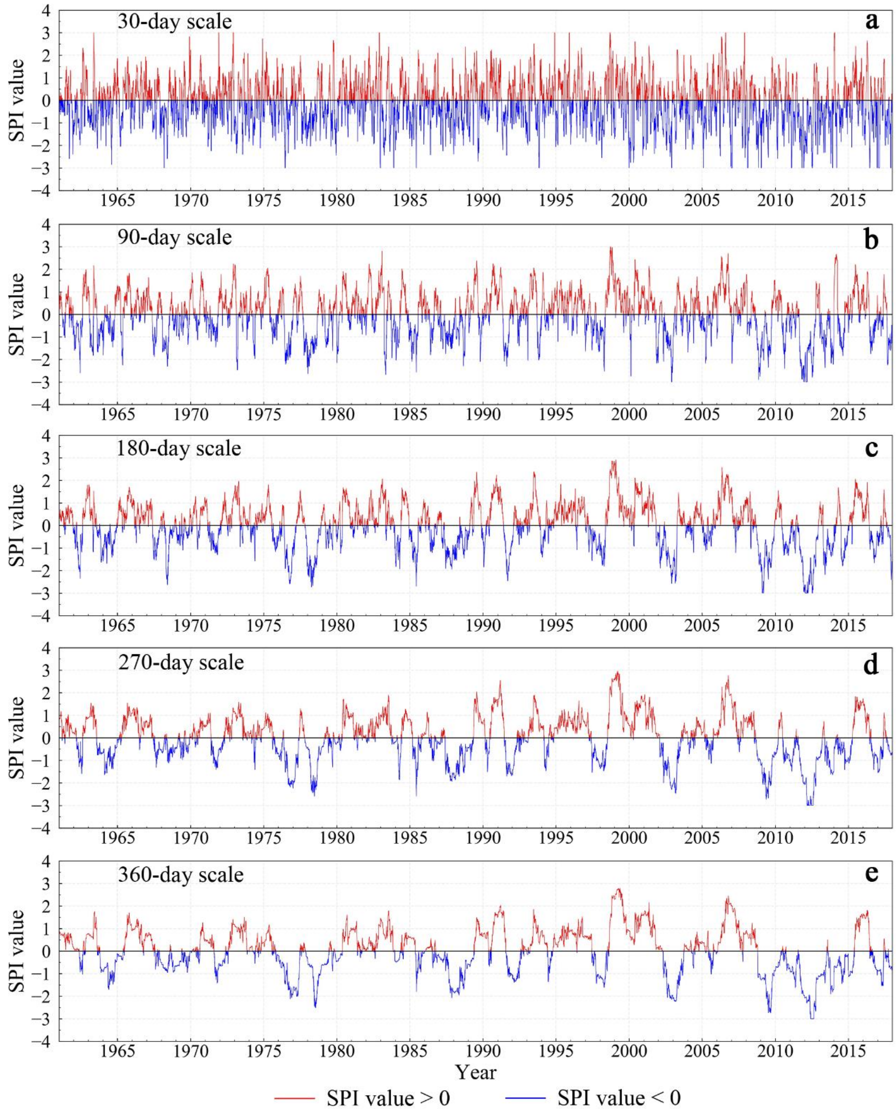

Figure 4. SPI curves of different time scales at station 56856 (Yunnan) from 1962 to 2018.

Compared with Yunnan and Henan, Fujian has plenty of rainfall, but droughts still occur frequently. As shown in Fig 5, the SPI curve at the monthly scale was greatly

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affected by short-term precipitation, and no obvious drought phenomenon was detected at the station 58847 (Fujian). However, the SPI curves of 3-month, 6-month, 9-month and 12-month time scale all showed that there were drought phenomena of different degrees in 1963, 1977, 1971, 1970, 1980, 1983, 1986, 1991, 1995, 2003 and 2004. This is identical to the records of *China Meteorological Disaster Dictionary* and *China Meteorological Disaster Yearbook*.

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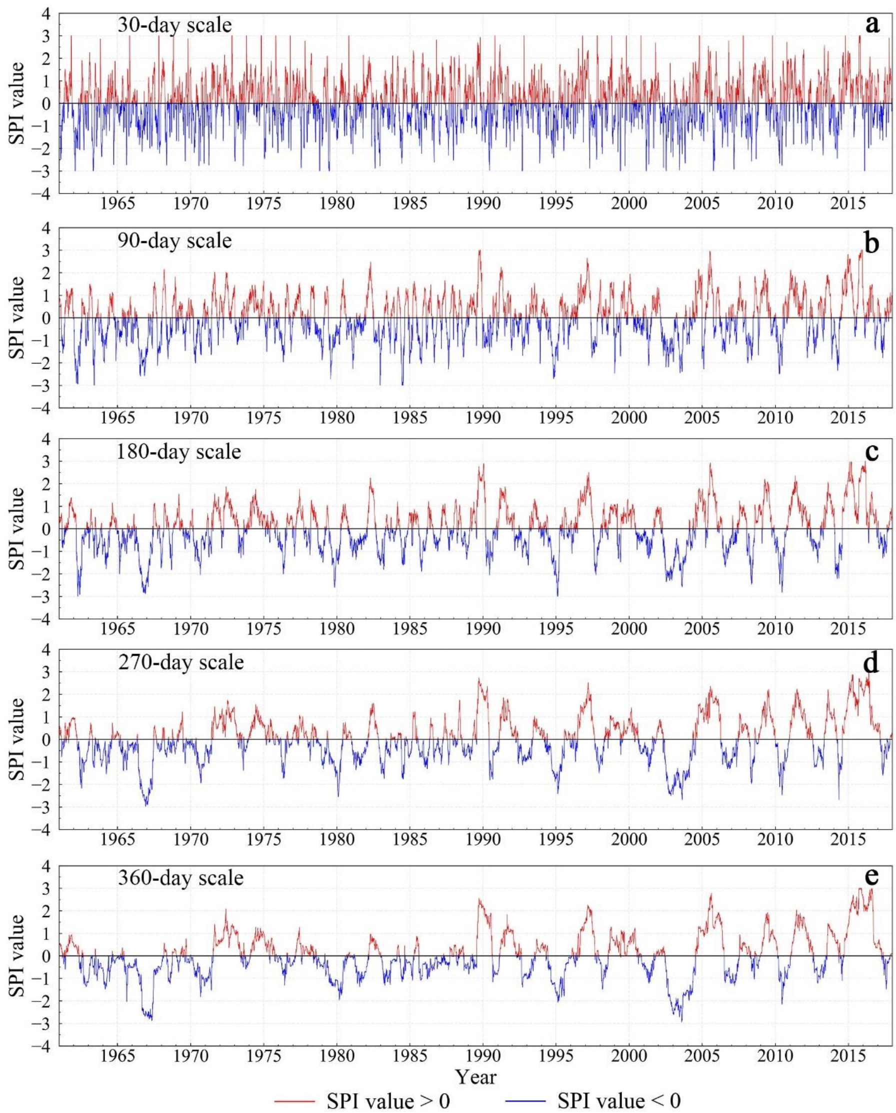

Figure 5. SPI curves of different time scales at station 58847 (Fujian) from 1962 to 2018.

3.2 Spatial Distribution of Drought Characteristics

Fig 6 shows the spatial distribution of variables ATDS and its trends of 484 stations in mainland China. The lower the ATDS value, the stronger the drought severity

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accumulated over the years and the more severe the drought suffered by the station. The ATDS values of most stations are concentrated between -130 and -121. The Xinjiang region in northwestern China and the provinces of Hebei and Shanxi in the central part of China suffered more severe droughts, with The ATDS values between -155 and -526. In general, the drought in northern China is more severe than in the south. However, compared with other areas in northern China, the drought in Heilongjiang and Jilin in the northeast is relatively mild (Fig 6a). The multi-year trend of variable ATDS in the study area is not very significant. The drought in Xinjiang, Qinghai and other places in northwestern China has eased, and the trend value is more than 30, *P*<0.05 (Fig 6b).

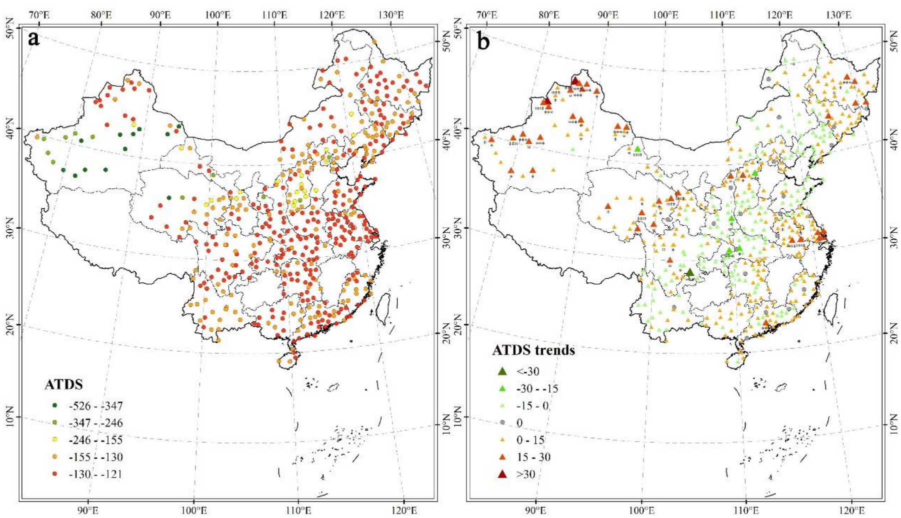

Figure 6. (a) The distribution of ATDS in the study area. (b) The distribution of the changing trends of ATDS ("***" means *P*-value < 0.001, "**" means *P*-value <0.01, and "*" means *P*-value < 0.05).

The variable ATDD represents the duration of the annual average drought event at

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each station, and has similar spatial distribution characteristics to the variable ATDS. Among them, the ATDD value of some stations in the Xinjiang region of northwestern China ranges from 196 to 279. Even in the southern regions with abundant rainfall, the ATDD values of most stations are between 103 and 112, which shows that most sites are suffering from drought (Fig 7a). In addition, the multi-year trend of ATDD shows that the drought duration of some stations in the southwest, southeast and northeast regions of China has been significantly reduced, while the drought duration of some stations in the central and southwestern regions has increased significantly (Fig 7b).

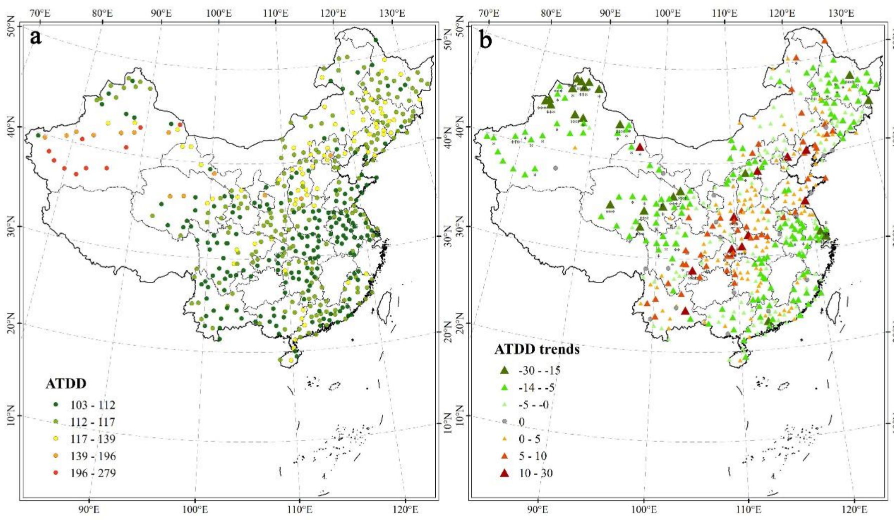

Figure 7. (a) The distribution of ATDD in the study area. (b) The distribution of the changing trends of ATDD ("***" means *P*-value < 0.001, "**" means *P*-value <0.01, and "*" means *P*-value < 0.05).

As shown in Fig 8, the spatial distribution pattern of variable ATDF is different from ATDS and ATDD. The frequency of drought in some stations in the Xinjiang

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region of northwest China is not high with a low ATDF, while the stations in the northeastern and southwestern regions show a higher frequency of drought events and higher ATDF values. Combining the characteristics of the ATDS and ATDD variables, we can see that the drought events at some stations in the Xinjiang region of northwest China are characterized by high severity, long duration but low frequency, while the drought events at some stations in the northeastern region are characterized by low severity, short duration but high frequency (Fig 8a). In general, the multi-year trend of ATDF is not significant (Fig 8b).

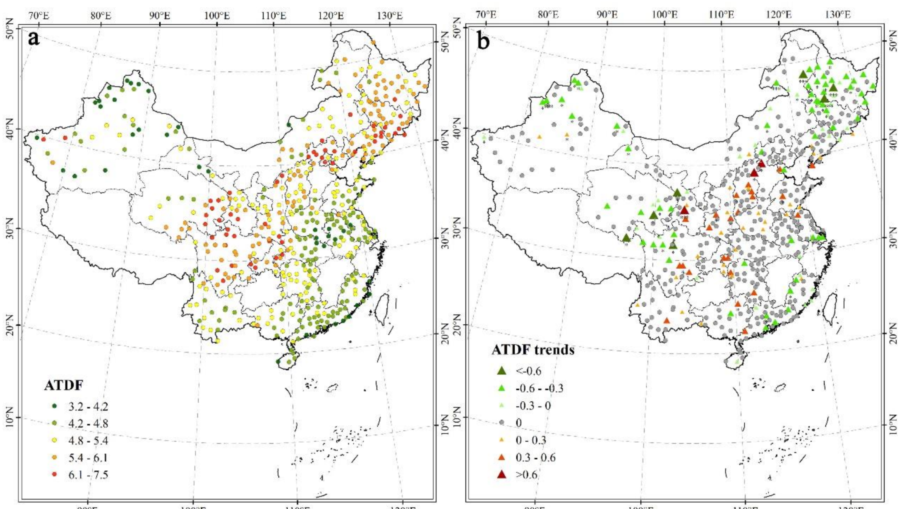

Figure 8. (a) The distribution of ATDF in the study area. (b) The distribution of the changing trends of ATDF ("***" means P-value < 0.001, "**" means P-value <0.01, and "*" means P-value < 0.05).

4. Discussion

SPI is the most commonly used indicator worldwide for detecting and

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characterizing droughts, because it requires fewer parameters to calculate and can better reflect drought intensity and duration on different time scales (Yang et al., 2019). SPI has been applied in many fields such as ecology, meteorology, agriculture, water conservancy and so on (Kumar et al., 2021; Javed et al., 2021). But the previous SPI can't monitor the drought below one month scale, and can't accurately identify the exact time of drought events. Therefore, based on the commonly used monthly SPI (Stagge et al., 2015) and the daily SPEI algorithm in our previous study (Wang et al., 2021b), we developed the new daily SPI dataset, which makes up for the lack of previous monthly SPI. In addition, the selection of parameter probability distribution is the key to calculate SPI, because the appropriate parameter probability distribution can improve the accuracy of SPI monitoring drought events (Sienz et al., 2012). We used the gamma probability distribution, which was validated in Europe and will be verified in a larger area in the future, to calculate the SPI (Stagge et al., 2015).

To verify the validity of our daily SPI dataset, we selected three typical stations in different regions, including 53898 (Henan), 58847 (Fujian), 56856 (Yunnan), and analyzed the characteristics of drought events at different stations and different time scales. The results show that the SPI curve of a longer time scale captured drought events lasted longer, which mainly because that the long-time scale SPI curve was not sensitive to short-term precipitation. In short, the drought events captured by the new SPI we developed were consistent with those recorded in *the Chinese Disaster Dictionary* and *the Chinese Disaster Yearbook*, and can be applied to drought research in many different fields such as meteorology, agriculture, hydrology, and society.

SPI of different time scales is closely related to different types of drought (1-month timescale vs. meteorological drought, 3-6-month timescale vs. agricultural drought, 12-month timescale vs. hydrological drought, and 24-month timescale vs. socioeconomic drought) (Vicente-Serrano et al., 2010a). We took the 3-month time scale SPI, which characterizes soil and agricultural droughts, as an instance to analyze in detail. The results show that the characteristics of drought events in mainland China did not increase significantly, while some stations in the northwest, northeast and southeast regions showed signs of drought reduction, which is identical to previous studies (Cai et al., 2020; Han et al., 2020). Although there was no obvious drought intensification or mitigation in Hebei, Shanxi and other places in central China, the drought was serious. Moreover, this region is the food production base of China, and further attention should be paid to drought disaster in this region to avoid serious impact on agricultural production. According to our 3-month scale SPI dataset, the characteristics of drought events in northwest Xinjiang were completely opposite to those in Northeast China, which have been reported in the past (Cai et al., 2020; Khan et al., 2020). The causes of different drought events in different regions may be related to location, topography, climate and other factors (Liu et al., 2021), which need to be further analyzed and discussed with more data in the future.

In short, drought has a profound impact on human beings, and modern societies are less inclined to accept the conventional risks of drought, so it is necessary to make as accurate an assessment and monitoring of drought as possible. The estimation of drought will continue to occupy the attention of ecologist, meteorologist, hydrologist,

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etc. The new daily SPI data we developed is able to effectively identify multiple types of drought and accurately capture the beginning and end of drought events. It can provide data base and conclusion reference for the research in related fields that mentioned before.

5. Data Availability

The new daily SPI data set developed by us contains SPI values of five time scales (1-month, 3-month, 6-month, 12-month, 24-month) from 484 weather stations in Chinese mainland from 1961 to 2018. The daily value SPI of each time scale was stored in a separate folder in csv format. All daily SPI dataset, including the data description, can be freely accessed through figshare (Wang et al., 2021a), and available at doi: doi.org/10.6084/m9.figshare.14135144.

6. Summary

Using multi-year daily precipitation data from 484 stations in mainland China, combined with the commonly used monthly SPI algorithm, a daily SPI data set was established for the first time. Our research fills the gaps in daily SPI research and makes up for the lack of monthly SPI in capturing short-term droughts. The research results showed that the drought events detected by our new daily SPI were consistent with the records. Taking the 3-month time scale of SPI as an example, the spatial distribution characteristics of drought events at each site were also consistent with the results of previous studies. In short, the new daily SPI data can be applied to various types of drought research (meteorological drought, agricultural drought, hydrological drought). In addition, we will make the new daily SPI data set freely available to the public, hoping to provide a convenience to researchers in different fields.

Author contributions.

QFW led the study, developed the method, and wrote the manuscript with input from all the authors. RRZ assisted in writing the manuscript. YPQ, and JYZ discussed the results and revised the manuscript. All the authors contributed to the final manuscript. XPW, XZZ, BYR, XHL and DHZ collected and analyzed 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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