Spatiotemporal Characteristics of Drought in the Heihe River Basin Based on the Extreme-Point Symmetric Mode Decomposition Method

Kai Feng¹ · Xiaoling Su^{1,2}

Published online: 9 December 2019
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Abstract Assessment of spatiotemporal characteristics of drought under climate change is significant for drought mitigation. In this study, the standardized precipitation evapotranspiration index (SPEI) calculated at different timescales was adopted to describe the drought conditions in the Heihe River Basin (HRB) from 1961 to 2014. The period characteristics and spatiotemporal distribution of drought were analyzed by using the extreme-point symmetric mode decomposition (ESMD) and inverse distance weight interpolation methods. Four main results were obtained. (1) The SPEI series of the upper reaches of the HRB at different timescales showed an upward trend (not significant) during 1961–2014. In the middle and lower reaches, the SPEI series exhibited significant downward trends. (2) The annual SPEI series of the lower reaches was decomposed through the ESMD method and exhibited a fluctuating downward trend as a whole. The oscillation showed quasi-3.4-year and quasi-4.5-year periods in the interannual variation, while a quasi-13.5-year period occurred in the interdecadal variation. The interannual period plays a leading role in drought variation across the HRB. (3) The entire research period was divided into three subperiods by the Bernaola–Galvan segmentation algorithm: 1961–1966, 1967–1996, and 1997–2014. The spring drought frequency and autumn drought intensity arrived at their maxima in the lower reaches during 1997–2014, with

values of 72.22% and 1.56, respectively. The high frequency and intensity areas of spring, summer, and autumn drought moved from the middle-upper reaches to the middle-lower reaches of the HRB during 1961–2014. (4) Compared to the wavelet transform, the ESMD method has self-adaptability for signal decomposition and is more accurate for drought period analysis. Extreme-point symmetric mode decomposition is a more efficient decomposition method for nonlinear and nonstationary time series and has important significance for revealing the complicated change features of climate systems.

Keywords China · Drought · Heihe River Basin · Spatiotemporal drought analysis

1 Introduction

Drought is among the most destructive and complicated natural hazards and is caused by a persistent shortage of precipitation or excessive evapotranspiration over an extended period of time (Portela et al. 2015; Deo et al. 2017). Drought is characteristically slow to develop and recurrent. When drought occurs, it has serious impacts on local socioeconomic development, ecology, and water resources (Li, Su et al. 2013; Zhou et al. 2017). Although droughts occur in virtually all climatic areas and cannot be avoided, drought characteristics can be analyzed accurately and quantified objectively by a drought index based on hydrometeorological monitoring data, which plays a key role in drought emergency program formulation. The onset and ending times, duration, and intensity of drought can be investigated quantitatively through drought indices. The spatial and temporal characteristics of drought can be identified, and an early warning system can be established.

✉ Xiaoling Su
xiaolingsu@nwfufu.edu.cn

¹ College of Water Resources and Architectural Engineering, Northwest A & F University, Yangling 712100, China

² Key Laboratory of Agricultural Soil and Water Engineering in Arid and Semiarid Areas, Ministry of Education, Northwest A & F University, Yangling 712100, China

In recent decades, various drought indices have been developed for drought survey and characterization. Among them, the standardized precipitation index (SPI) and the Palmer drought severity index (PDSI) are especially popular around the world (Yao et al. 2017; Yang et al. 2018), but they also have many deficiencies. For example, the calculation of the SPI only uses precipitation and does not consider the influence of temperature variation (Shen et al. 2017); the spatial comparability of the PDSI is limited, and the results are heavily dependent on data calibration (Sheffield et al. 2009; Yu et al. 2014; Guo et al. 2018). To address these drawbacks, the standardized precipitation evapotranspiration index (SPEI), which combines the advantages of the SPI and PDSI, was proposed by Vicente-Serrano et al. (2010). The SPEI not only considers the response of drought to temperature but also retains spatial comparability and multiple temporal scales, which improves the accuracy of drought monitoring and promotes its application as a robust drought survey tool. Since the SPEI was proposed, it has been frequently applied to anatomizing drought features and change tendencies at regional scales (Liu, Ren et al. 2016; Mallya et al. 2016; Zuo et al. 2018; Gao et al. 2017). Tong et al. (2018) applied the SPEI to identify the variations and patterns of drought on the Mongolian Plateau during 1980–2014. Yang et al. (2016) discussed the temporal variability and spatial distribution of different drought levels in the Haihe River Basin during 1961–2010 by using the SPEI. The results showed that the SPEI can monitor drought effectively in the context of climate change.

In previous studies, the wavelet transforms and Mann–Kendall (M–K) test have been widely conducted to identify periodic oscillations and temporal trends in time series of drought (Zhang et al. 2015; Jia and Pan 2016; Liu, Wang et al. 2016; Wu et al. 2016). Wavelet transform is suitable for linear and nonstationary time series because it is based on the principle of linear superposition (Li, Wang et al. 2013; Wang and Li 2013). The hydrometeorological data in a complex, nonlinear coupled system cannot satisfy the prerequisites, and the selection of wavelet bases plays a decisive role in the process of drought cycle analysis. With the development of detection technology for long time series, the extreme-point symmetric mode decomposition (ESMD) that is suitable for nonlinear and nonstationary time series was proposed by Wang and Li (2013). The oscillatory components of different scales and trend components of the original time sequence can be gradually decomposed through ESMD, which considerably improves the assessment accuracy of drought cycles and trends. In recent years, ESMD has been widely utilized in the study of time series under climate change in China (Lei et al. 2016; Lin et al. 2017; Qin et al. 2017). These studies suggest that the ESMD method can effectively reveal

variations in long-term time sequences and can be used for the diagnosis of complex nonlinear and nonstationary signal changes.

The Heihe River Basin (HRB) is located in the inland area of northwest China. Due to the influence of different types of climate, the temperature and precipitation in the HRB show significant zonality, and partitioning the basin in space is essential for drought research. Regional drought has displayed temporal volatility and nonstationarity with the effects of climate change and human activities. Thus, studying different periods is important to understand the tendency of drought evolution more accurately (Huang, Chang, et al. 2015). Research on drought in the HRB has been reported occasionally (Huang et al. 2016; Zhong et al. 2017), but a regional and time-varying drought assessment across the HRB has not been carried out. Therefore, in this study, the HRB is divided into three research areas—the upper, middle, and lower reaches—and the study period is divided into three subperiods, that is 1961–1966, 1967–1996, and 1997–2014, based on the Bernola–Galvan (B–G) segmentation algorithm. Using the ESMD method and geographic information system (GIS) techniques to analyze the spatiotemporal characteristics of drought during 1961–2014 provides a valuable reference for drought mitigation in the HRB.

2 Materials and Methods

The study area is located in northwestern China, and often suffers from drought. The monthly data of meteorological stations obtained from the China Meteorological Data Sharing Service System are used in this study.

2.1 The Heihe River Basin Study Area

The HRB contains the second-largest inland river in China and is located between 98°–101°30' E and 38°–42° N. The basin crosses Qinghai Province, Gansu Province, and Inner Mongolia Autonomous Region. The river originates from the Qilian Mountains in the south of the study area and has a total length of 821 km, and the HRB covers an area of approximately 14.29×10^4 km². Yingluoxia and Zhengyixia are two hydrological control stations (Fig. 1). The regions above Yingluoxia are the upper reaches. The middle reaches range from Yingluoxia to Zhengyixia, while the area below Zhengyixia encompasses the lower reaches. The HRB is in an arid environment, with a dry climate, sparse and concentrated precipitation, strong solar radiation, and large annual and daily variabilities in temperature. The mean annual precipitation and the average annual temperature during 1961–2014 were 193.9 mm and 4.8 °C, respectively. In recent years, the changes in

Fig. 1 Meteorological and hydrological stations in the Heihe River Basin, China. River basin upper reaches: Mountain pass to Yingluoxia. River basin middle reaches: Yingluoxia to Zhengyixia. River basin lower reaches: Area north of Zhengyixia. 1. Mazongshan; 2. Yumenzen; 3. Dingxin; 4. Jiuquan; 5. Gaotai; 6. Linze; 7. Sunan; 8. Zhangye; 9. Minle; 10. Shandan; 11. Yongchang; 12. Ejinaqi; 13. Tuolei; 14. Yeniugou; 15. Qilian

precipitation and temperature have contributed to increasingly severe drought issues, especially seasonal drought.

2.2 Data

In this research, the monthly precipitation and temperature data observed at 15 meteorological stations in and around the HRB during 1961–2014 were selected to calculate the SPEI. The data of 12 meteorological stations were obtained from the China Meteorological Data Sharing Service System,¹ while the data of the remaining three meteorological stations, Minle, Linze, and Sunan, were provided by the Gansu Meteorological Bureau. The data series were carefully checked, and no data were missing.

To ensure the comparability and reliability of the results, three typical stations for each subarea were selected to analyze the temporal features (Qilian, Yeniugou, and Tuolei stations for the upper reaches; Gaotai, Zhangye, and Shandan stations for the middle reaches; and Dingxin, Jiuquan, and Ejinaqi stations for the lower reaches), and the 15 stations were used to interpolate for spatial characteristics analysis. Figure 1 shows the locations of the meteorological and hydrological stations.

2.3 Methods

The research methods include extreme-point symmetric mode decomposition (ESMD) and fast Fourier transform (FFT) for calculating drought period, the Bernaola–Galvan (B–G) segmentation algorithm for determining drought mutation points, and the Mann–Kendall (M–K) trend test

for estimating drought variation trend during the study period.

2.3.1 Standardized Precipitation Evapotranspiration Index (SPEI)

The SPEI is an extension of the SPI. The principle of the SPEI is to utilize the difference degree between precipitation and evapotranspiration to represent regional drought (Vicente-Serrano et al. 2010; Ming et al. 2015). The three calculation steps are (Shen et al. 2017): (1) the potential evapotranspiration (PET) is calculated by the Thornthwaite method (Liu et al. 2012), and the water balance D (precipitation minus PET) is calculated; (2) the probability distribution of D is fitted to a log–logistic probability density function; and (3) after transforming the cumulative probability to a standard normal distribution, the SPEI value can be calculated.

Negative SPEI values indicate that the climate condition is dry (drought), while positive SPEI values represent a wet climate condition, and SPEI values near zero refer to normal climate conditions. Following Yang et al. (2016), the classifications of drought severity based on SPEI are given in Table 1, and in our study droughts are defined as when the SPEI value is less than -0.5 .

2.3.2 Extreme-Point Symmetric Mode Decomposition (ESMD)

The ESMD method was proposed by Wang and Li (2013). It utilizes the concept of empirical mode decomposition (EMD) and least squares to optimize the final vestigial mode, thereby engendering an optimal adaptive global mean curve and determining the best selection times. The ESMD is among the newest methods to extract the trend and period of time series and can be adopted to smoothly process complicated time series. The inherently different scale oscillations and trend components of the original time sequence may be gradually extracted (Li, Wang et al. 2013). Moreover, the ESMD method can intuitively reflect the time-varying properties of amplitude and frequency of each mode.

In this research, the ESMD method was chosen to study the cyclic characteristics of drought in the HRB. The specific steps are (Wang and Li 2013; Qin et al. 2017):

1. Find all local extreme points (maxima points and minima points) of the series Y and order them by $E_i (1 \leq i \leq n)$.
2. Connect all adjacent E_i with line segments and mark their midpoints by $F_i (1 \leq i \leq n - 1)$. Add left and right boundary midpoints F_0 and F_n .

¹ <http://data.cma.cn/>.

Table 1 Drought level classification for the Heihe River Basin

Grade	Drought severity	SPEI value
I	No drought	$-0.5 < \text{SPEI}$
II	Light drought	$-1.0 < \text{SPEI} \leq -0.5$
III	Moderate drought	$-1.5 < \text{SPEI} \leq -1.0$
IV	Severe drought	$-2.0 < \text{SPEI} \leq -1.5$
V	Extreme drought	$\text{SPEI} \leq -2.0$

- Construct p interpolating curves $L_1, \dots, L_p$ ($p \geq 1$) with all $n+1$ midpoints; calculate their mean value by $L^* = (L_1 + \dots + L_p)/p$.
- Repeat the above three steps on $Y - L^*$ until $|L^*| \leq \varepsilon$ (ε is a permitted error) or the sifting times arrive at a preset maximum number K . Then, the first mode IMF_1 can be obtained.
- Repeat the above four steps on the residual $Y - \text{IMF}_1$ and obtain $\text{IMF}_2, \text{IMF}_3, \dots$ until the last residual R is a single signal or with no more than a certain number of extreme points.
- Change the maximum number K on a finite integer interval $[K_{\min}, K_{\max}]$ and repeat the above five steps. Then, calculate the variance σ^2 of $Y - R$ and plot a figure with σ/σ_0 and K ; here, σ_0 is the standard deviation of Y .
- Find the number K_0 that accords with the minimum σ/σ_0 on $[K_{\min}, K_{\max}]$. Then, use this K_0 to repeat the previous five steps and output all modes. Finally, the last residual R is actually an optimal adaptive global mean curve.

2.3.3 Bernaola–Galvan (B–G) Segmentation Algorithm

Several statistical detection methods for identifying mutation points of sequences exist, such as the Mann–Kendall test, the sliding T test, and the sliding F test (Salami et al. 2014; Zhang et al. 2014). All of these tests are actualized based on the assumption of a linear stationary series, which leads to deviations in the process of detecting the change points of nonlinear and nonstationary sequences (Huang, Huang et al. 2015). Consequently, the B–G segmentation algorithm was highly recommended by Bernaola–Galvan et al. (2001). Compared with traditional methods, this method can partition a nonstationary time series into several stationary segments and effectively capture the change points of the time series. The scales of the decomposed segments are variable and are not limited by the method itself (Li et al. 2010). Therefore, the B–G segmentation algorithm was employed to catch the mutation years and to analyze the characteristics of droughts in subseries.

2.3.4 Mann–Kendall (M–K) Trend Test

The Mann–Kendall trend test (Mann 1945; Kendall 1975) was used to estimate drought variation trends from 1961 to 2014. This method has been frequently applied to determine the existence of statistically significant trends in hydrometeorological time series (Zhang and Hu 2018). The test statistic Z was computed as follows:

$$Z = \begin{cases} (S-1)/\sqrt{\text{VAR}(S)} & S > 0 \\ 0 & S = 0 \\ (S+1)/\sqrt{\text{VAR}(S)} & S < 0 \end{cases} \quad (1)$$

where S was calculated as follows:

$$S = \sum_{k=1}^{n-1} \sum_{j=k+1}^n \text{Sgn}(X_j - X_k) \\ = \begin{cases} \text{Sgn}(X_j - X_k) = 1 & (X_j - X_k) < 0 \\ \text{Sgn}(X_j - X_k) = 0 & (X_j - X_k) = 0 \\ \text{Sgn}(X_j - X_k) = -1 & (X_j - X_k) > 0 \end{cases} \quad (2)$$

For statistic Z , a positive value indicated an upward trend, while a negative value indicated a downward trend. The null hypothesis (no trend) is rejected at the 0.1 significance level, if $|Z| > 1.64$, at the 0.05 significance level, if $|Z| > 1.96$, and at the 0.01 significance level, if $|Z| > 2.58$.

3 Results

This study discussed the period characteristics and spatiotemporal distribution of droughts in the HRB during 1961–2014. We first analyzed the trend of temporal change of drought at different timescales in the subareas, and then examined the drought period characteristics in the HRB.

3.1 Temporal Characteristics of Drought

The variations in mean SPEI values at different timescales in the three subareas of the HRB are given in Fig. 2. Based on the linear trend, the SPEI series at different timescales (monthly, seasonal, and annual) in the upper reaches of the HRB represent fluctuating upward trends with gradients of 0.0005/10 a, 0.004/10 a, and 0.039/10 a, respectively. The monthly, seasonal, and annual SPEI sequences in the middle and lower reaches of the HRB exhibit downward trends with decreasing slopes of $-0.007/10$ a, $-0.023/10$ a, and $-0.26/10$ a; and $-0.011/10$ a, $-0.047/10$ a, and $-0.406/10$ a, respectively. In addition, all the changing rates of the annual scale SPEI sequences arrive at the maximum.

The M–K test is applied to analyze the trend of SPEI series at different timescales in the three subareas of the

Fig. 2 The standardized precipitation evapotranspiration index (SPEI) values at different timescales in the upper, middle, and lower reaches of the Heihe River Basin during 1961–2014

HRB. The statistical values are listed in Table 2. The SPEI series in the upper reaches represent upward trends with no significant difference. The seasonal scale SPEI in the middle reaches is significant at the 0.1 probability level, and the other sequences are significant at the 0.01 probability level, which illustrates that droughts in the middle and lower reaches show a significant downward trend during 1961–2014.

Taking the annual scale SPEI as an example, drought is judged to have occurred when the value is less than -0.5 . Figure 2 shows that the number of drought occurrences in the upper reaches was 15 during 1961–2014, that most of the droughts happened before 2000, and that the most

severe drought year was 1997 (SPEI = -1.62). A majority of droughts in the middle and lower reaches occurred after 2000, and the minimum values were -2.1 in 2013 and -1.97 in 2001.

3.2 Characteristics of the Drought Periods and Variation Trends

Taking the annual scale SPEI sequence of the lower reaches as an example, the sequence is decomposed through the ESMD method to acquire the characteristics of the drought period and the variation trends at the interannual and interdecadal scales.

In the decomposition process, when the variance ratio reaches a minimum, the ESMD method stops automatically. Here, R is the optimal adaptive global mean line of the entire data, and the corresponding decomposition is also optimal. Finally, three intrinsic mode function (IMF) components (IMF1–3) and one trend component (R) can be obtained (Fig. 3). Usually, each IMF component reflects the oscillation characteristics from high frequency to low frequency at different timescales, and the trend component represents the tendency of the original data over time.

As seen from the trend component in Fig. 3, the SPEI series shows a downward trend as a whole. A slight upward

Table 2 Temporal trends of drought at different timescales in the Heihe River Basin subareas during 1961–2014

Timescale	M–K statistical value		
	Upper reaches	Middle reaches	Lower reaches
Monthly	0.49	– 2.64	– 5.48
Seasonal	0.82	– 1.81	– 4.25
Annual	0.64	– 2.97	– 4.48

Note: Positive values indicate an increasing dry trend, or the opposite. If IMK value ≥ 1.96 , then the dry or wet trend is significant at a significance level of 95%. If IMK value ≥ 2.58 , then the dry or wet trend is significant at a confidence level of 99%

Fig. 3 The intrinsic mode function (IMF) and trend components of annual scale standardized precipitation evapotranspiration index (SPEI) values based on extreme-point symmetric mode decomposition (ESMD) in the lower reaches of the Heihe River Basin during 1961–2014

trend is apparent from 2004 to 2011, followed by another downward trend.

The fast Fourier transform (FFT) method is utilized to calculate the mean period of each component to reflect the oscillation on inherently different characteristic scales in the original series. Figure 4 demonstrates the power-period graph of IMF components of annual scale SPEI series and shows that the SPEI series of the HRB during 1961–2014 had quasi-3.4-year and quasi-4.5-year cycles in the interannual variations, while a quasi-13.5-year period occurred in the interdecadal variations. The effect of each component fluctuation frequency and amplitude on the raw SPEI series can be expressed by the variance contribution rate. The variance contribution rate and correlation coefficient of each component to SPEI series are listed in Table 3.

Combining Fig. 4 and Table 3, the contribution of IMF1 to the SPEI sequence variance of the quasi-3.4-year cycle is the greatest, reaching 35.01%; the correlation coefficient is 0.527, which passes the significance test at the 99% confidence level, and the vibration signal is very obvious. IMF2 contributes 8.36% to the SPEI sequence variance of the quasi-4.5-year cycle, and the correlation coefficient is

Table 3 The variance contribution rate and correlation coefficient of each component of the standardized precipitation evapotranspiration index (SPEI) series in the Heihe River Basin during 1961–2014

Mode component	IMF1	IMF2	IMF3	R
Period (year)	3.4	4.5	13.5	
Contribution rate (%)	35.01	8.36	5.36	51.27
Correlation coefficient	0.527**	0.201	0.245*	0.728**

* Means the results reached a significance level of 0.1

** Means the results reached a significance level of 0.01

0.201. The contribution of IMF3 to the SPEI sequence variance of the quasi-13.5-year cycle is 5.36%, and the correlation coefficient is 0.245, which is significant at the 0.1 probability level, suggesting that the amplitude and instability of variation decrease at this timescale. Furthermore, the interannual cycles (quasi-3.4-year and quasi-4.5-year cycles) play leading roles in drought variation across the HRB.

Figure 5 illustrates the interannual SPEI sequence variation in comparison with the original SPEI sequence in the lower reaches of the HRB. The reconstructed interannual SPEI series can filter out the vibration of the interdecadal scale and characterize the trend of interannual change accurately. The oscillation trend between the reconstructed interannual SPEI sequence and the original SPEI series remains basically consistent, which can precisely describe the fluctuation of the raw SPEI sequence and more strongly prove that the interannual vibration occupies the dominant position in the variation of the SPEI sequence.

Figure 6a–c show the overall trends at different time-scales based on ESMD in the HRB during 1961–2014. The SPEI series at different timescales in each subarea represents different change tendencies, indicating that drought characteristics differ in the upper, middle, and lower reaches of the HRB.

Fig. 4 The power-period graphs of intrinsic mode function (IMF) components of annual scale standardized precipitation evapotranspiration index (SPEI) series in the Heihe River Basin during 1961–2014

Fig. 5 The comparison of change trends between the interannual standardized precipitation evapotranspiration index (SPEI) sequence and the original SPEI series in the lower reaches of the Heihe River Basin during 1961–2014

Fig. 6 The overall trends at different timescales based on extreme-point symmetric mode decomposition (ESMD) in the Heihe River Basin during 1961–2014

3.3 Spatial Distribution Characteristics of Drought

Based on the identification of drought mutation points, the spatial distribution characteristics of seasonal drought

frequency and intensity are investigated in the three sub-periods during 1961–2014.

3.3.1 Drought Mutation Detection

The B–G segmentation algorithm is applied to detect the mutation points of annual scale SPEI series in the HRB. The results are portrayed in Fig. 7, and the confidence level value is 0.95.

Figure 7a–c illustrate the mutation points of annual scale SPEI series in the upper, middle, and lower reaches of the HRB. Figure 7a shows that no mutation occurs in the upper reaches. Two abrupt change points are captured in 1966 and 1996 in the middle reaches (Fig. 7b), where a mutation increase occurs in 1966 and a mutation decrease happens in 1996. Figure 7c demonstrates that the SPEI series of the lower reaches experience a mutation decrease in 1996. Therefore, the study period is divided into three subperiods: 1961–1966, 1967–1996, and 1997–2014. Then, the distribution characteristics of drought in the subperiods are researched, with the aim of understanding the properties of drought propagation and evolution in the HRB.

Fig. 7 The mutation points of annual scale interannual standardized precipitation evapotranspiration index (SPEI) series in the Heihe River Basin during 1961–2014

Table 4 Seasonal drought frequency (%) in the upper, middle, and lower reaches of the Heihe River Basin in the three time periods during 1961–2014

Season	1961–1966			1967–1996			1997–2014		
	Upper	Middle	Lower	Upper	Middle	Lower	Upper	Middle	Lower
Spring	0.00	5.56	0.00	27.78	20.00	13.33	51.85	57.41	72.22
Summer	72.22	50.00	33.33	26.67	12.22	14.44	33.33	53.70	64.81
Autumn	33.33	50.00	27.78	38.89	23.33	22.22	31.48	42.59	44.44
Winter	53.33	40.00	40.00	27.78	38.89	45.56	38.89	20.37	29.63

Fig. 8 Spatial distribution characteristics of the seasonal drought frequency in the Heihe River Basin in the three subperiods during 1961–2014

3.3.2 Spatial Distribution Characteristics of Drought Frequency

Evaluating the spatial characteristics of drought is vital for understanding droughts clearly (Andreadis et al. 2005). Thus, the spatial distribution variability of seasonal drought is further analyzed based on GIS techniques. The seasonal drought frequencies for the three time periods are listed in Table 4.

For the period 1961–1996, the spring drought frequencies in the upper, middle, and lower reaches are the lowest, with rates of 0%, 5.56%, and 0%, respectively. The occurrence rate of summer drought in the upper reaches culminates at 72.22%. In 1967–1996, the drought frequency displays downward trends from the upper to lower reaches in spring and autumn and expresses an upward tendency in winter. For 1997–2014, the drought frequency is generally higher than for 1961–1966 and 1967–1996, and the spring drought frequency in the lower reaches has its highest value. The drought frequencies in the middle

and lower reaches have a decreasing trend from spring to winter.

Figure 8 illustrates the spatial distribution features of seasonal drought frequency in the three time periods. The seasonal drought frequency in the HRB exhibited remarkable spatial distribution differences. The high-frequency area of spring drought moved from the upper to the lower reaches during 1961–2014, while the spatial distributions of summer, autumn, and winter drought frequency demonstrated oscillations to different extents in the three time periods. The occurrence rate of summer drought in the middle-upper reaches was at high levels during 1961–1966. The upper reaches had a high summer drought occurrence in 1967–1996. The high-frequency area shifted to the middle-lower reaches in 1997–2014. The middle-upper reaches of the HRB are the areas where autumn drought occurred with a high ratio in 1961–1966 and 1967–1996. The area with a higher autumn drought frequency is mainly located in the lower reaches rather than in the middle-upper reaches in 1997–2014. Winter drought was most likely to occur in the middle-lower reaches in 1961–1966, while

winter drought had a low occurrence rate in the upper reaches in 1967–1996.

In summary, the range of high-frequency seasonal drought expanded gradually, and the occurrence rate increased progressively during 1961–2014. The areas with high seasonal drought frequencies express contrasting conditions during the 1967–1996 and 1997–2014 time periods, which indicates that the seasonal drought occurrence across the HRB has been altered acutely by climate change.

3.3.3 Spatial Distribution Characteristics of Drought Intensity

Table 5 lists the seasonal drought intensities in the HRB in the three time periods. During 1961–1966, the most severe drought occurred in the upper reaches in winter with a value of 1.40, reaching a moderate drought level. The values of spring drought intensity in the middle and lower reaches were 0.2 and 0, respectively, which indicates the absence of drought. The intensities of spring and winter

drought represent a descending trend from the upper to lower reaches. The maximum spring drought intensity in the upper reaches was 1.2 during 1967–1996, and the drought intensities in the middle and lower reaches peaked in winter and autumn, respectively. During 1997–2014, the seasonal drought intensity in the HRB was generally higher than for the other two time periods, while autumn drought intensity in the lower reaches had a maximum of 1.56, which represents severe drought.

The spatial distribution characteristics of seasonal drought intensity in the three time periods are illustrated in Fig. 9. The areas of spring, autumn, and winter drought with high intensity are primarily situated in the middle-upper reaches in 1961–1966, while the summer drought had an extensive range with high intensity. Spring, summer, and winter drought occurred intensively in the middle-upper reaches during 1967–1996, and the high intensity area of autumn drought expanded to cover almost the whole HRB. During 1997–2014, the high intensity areas of spring, summer, and autumn drought were larger than those during 1961–1966 and 1967–1996, and the high intensity

Table 5 Seasonal drought intensities in the upper, middle, and lower reaches of the Heihe River Basin in the three subperiods during 1961–2014

Season	1961–1966			1967–1996			1997–2014		
	Upper	Middle	Lower	Upper	Middle	Lower	Upper	Middle	Lower
Spring	0.36	0.20	0.00	1.20	0.86	0.76	0.99	1.45	1.36
Summer	0.94	1.24	0.73	0.98	0.86	0.81	1.37	1.44	1.53
Autumn	0.86	0.85	1.03	1.02	0.94	1.03	1.33	1.49	1.56
Winter	1.40	1.19	1.15	1.00	1.10	1.00	1.01	1.26	1.04

Fig. 9 Spatial distribution characteristics of seasonal drought intensity in the Heihe River Basin in the three subperiods during 1961–2014

Fig. 10 Variation characteristics of precipitation and average temperature in the Heihe River Basin during 1961–2014

center of winter drought was located near Gaotai station in the middle reaches. During 1961–2014, areas where spring and autumn drought occurred intensively had a tendency to move from the upper to the lower reaches, and the intensity expressed an upward trend. The high intensity area of winter drought exhibited a downward trend.

4 Discussion

Global droughts have been increasing in recent years due to global climate change (Wang et al. 2018). Drought occurrence and change are remarkably influenced by local hydrological cycles. Globally, the average surface temperature has significantly increased with a gradient of $0.13 \pm 0.03^\circ/10$ a since 1950 (Jiang et al. 2015). However, the variation in precipitation represents more complicated spatial and temporal patterns in different climatic regions (Chen et al. 2011). Therefore, the drought evolution in the HRB could be attributed to the radically reduced precipitation or augmented evapotranspiration.

Feng et al. (2013) investigated the variability of drought under climate change in the HRB during 1961–2010. Their results showed that the drought tendency increases with further expansion of drought coverage and frequency of dryness/wetness alternations. Annual drought is shifting south-westward, and interannual drought is developing towards the north. These results are consistent with the conclusions of this study. Other research has emphasized that drought is highly related to decreased rainfall and increased temperature (Zhang et al. 2010).

The variation characteristics of precipitation and average temperature in the HRB during 1961–2014 are

illustrated in Fig. 10. Annual and seasonal precipitation in the upper, middle, and lower reaches is gradually decreasing. In contrast, the average temperature is stepwise increasing. This combination increases the evapotranspiration and aggravates the degree of water deficit, frequently leading to high-intensity drought.

In this study, the research period was divided into three stages based on the B–G method for the recent 54 years studied in the HRB: 1961–1966, 1967–1996, and 1997–2014. Three droughts occurred during 1961–1966 (mean SPEI of -0.17), two droughts occurred during 1967–1996 (mean SPEI of -0.43), and thirteen droughts occurred during 1997–2014 (mean SPEI of -0.67). Droughts during 1997–2014 were more severe than in the other two stages.

Continuous wavelet transform (CWT) analysis of the annual scale SPEI sequence in the lower reaches was carried out to explore the differences in time–frequency domains between ESMD and CWT with three wavelet basis types of db5, Haar, and mexh. The time–frequency distributions and variance diagrams for different wavelet basis transform coefficients are given in Fig. 11. The periodic characteristics of the SPEI sequence can be obtained from the diagrams. The order of periods can be determined according to the strong and weak signal oscillations.

Figure 11a shows that three apparent periodic oscillations exist with the db5 wavelet basis of 2–3 years, 9 years, and more than 25 years for the annual SPEI series. Under the Haar wavelet basis condition (Fig. 11b), three periodic oscillations emerge in the wavelet transform analysis of the annual SPEI sequence, at 3–4 years, 8–10 years, and more than 25 years. Figure 11c shows that the annual SPEI

Fig. 11 Time–frequency distributions and variance diagrams for different wavelet basis transform coefficients for the Heihe River Basin during 1961–2014

series has only an 18-year periodic oscillation through CWT analysis with the mexh wavelet basis. The periodic characteristics of sequences obtained by wavelet transform analysis using different wavelet bases notably display very large differences.

Through the comparative analysis, it can be observed that the ESMD method has self-adaptability for signal decomposition (does not designate the basic function in advance) and is more accurate for period calculation. However, the selection of wavelet basis has a significant effect on drought period detection through the wavelet transform.

By comparing the nonlinear trend component R with the linear trend of the original SPEI sequence, the overall variation properties of the annual SPEI series at different timescales in the HRB during 1961–2014 can be precisely reflected by the nonlinear trend and the interannual change trend through ESMD, while the traditional linear trend can neither reveal the variation of SPEI at different time stages nor identify the tendency change of large-scale structure. Evidently, ESMD is an efficient signal analysis method applicable to nonlinear and nonstationary time series, which extracts the interannual and interdecadal trends from observation sequences and meticulously describes the change process of drought events.

In summary, the wavelet transform is suitable for the linear and nonstationary time series. Moreover, the selection of the wavelet basis has a significant effect on the

period analysis. However, the ESMD method has self-adaptability for signal decomposition and does not designate the basic function in advance, which is applicable for nonlinear, nonstationary time series.

5 Conclusion

In this study, the SPEI was used to analyze the spatiotemporal characteristics of drought across the Heihe River Basin from 1961 to 2014. The interannual and interdecadal variations and the spatial change of drought in three subareas during three time periods were comprehensively investigated by utilizing the ESMD and GIS methods. The main conclusions are as follows:

1. The SPEI series at different timescales in the upper reaches of the Heihe River Basin showed an upward trend during 1961–2014, which had no significant difference. The SPEI series exhibited significant downward trends in the middle and lower reaches. The gradients of the annual scale series were highest at $0.039/10$ a, $-0.26/10$ a, and $-0.406/10$ a in the upper, middle, and lower reaches, respectively.
2. For the annual scale SPEI sequence of the lower reaches, the trend component R expresses that the SPEI series had a fluctuating downward trend, and the changes showed quasi-3.4-year and quasi-4.5-year cycles in the interannual variations, while a quasi-

13.5-year period occurred in the interdecadal variation. The interannual cycle played a leading role in drought variation across the HRB.

3. The spring drought frequency and autumn drought intensity were highest in the lower reaches during 1997–2014, with values of 72.22% and 1.56, respectively. At the same time, the high frequency and intensity of spring, summer, and autumn drought occurrences moved from the middle-upper reaches to the middle-lower reaches of the HRB during 1961–2014.
4. The ESMD is among the best time series decomposition methods applicable for nonlinear and nonstationary SPEI series. The ESMD extracts the interannual and interdecadal trends from the SPEI series and meticulously describes the change process of drought events under climate change. The ESMD method is more efficient for the decomposition of interannual scale variations and can accurately reflect the intrinsic features of drought events.

Acknowledgements We are grateful for the grant support from the National Natural Science Foundation of China (51879222 and 91425302) and the National Key Research and Development Program during the 13th Five-Year Plan in China (2016YFC0401306).

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References

- Andreadis, K.M., E.A. Clark, A.W. Wood, A.F. Hamlet, and D.P. Lettenmaier. 2005. Twentieth-century drought in the conterminous United States. *Journal of Hydrometeorology* 6(6): 985–1001.
- Bernaola-Galván, P., P.C. Ivanov, L.A. Amaral, and H.E. Stanley. 2001. Scale invariance in the nonstationarity of human heart rate. *Physical Review Letters* 87(16): Article 168105.
- Chen, F.H., W. Huang, L.Y. Jin, J.H. Chen, and J.S. Wang. 2011. Spatiotemporal precipitation variations in the arid Central Asia in the context of global warming. *Science China Earth Sciences* 54(12): 1812–1821.
- Deo, R.C., H.R. Byun, J.F. Adamowski, and K. Begum. 2017. Application of effective drought index for quantification of meteorological drought events: A case study in Australia. *Theoretical and Applied Climatology* 128(1–2): 359–379.
- Feng, J., D. Yan, and C. Li. 2013. Evolutionary trends of drought under climate change in the Heihe River Basin, Northwest China. *International Journal of Food Agriculture & Environment* 11(1): 1025–1031.
- Gao, X., Q. Zhao, X. Zhao, P. Wu, X. Gao, and M. Sun. 2017. Temporal and spatial evolution of the standardized precipitation evapotranspiration index (SPEI) in the Loess Plateau under climate change from 2001 to 2050. *Science of the Total Environment* 595: 191–200.
- Guo, H., A.M. Bao, T. Liu, G. Jiapaer, F. Ndayisaba, L.L. Jiang, A. Kurban, and P.D. Maeyer. 2018. Spatial and temporal characteristics of droughts in Central Asia during 1966–2015. *Science of the Total Environment* 624: 1523–1538.
- Huang, S.Z., J.X. Chang, G.Y. Leng, and Q. Huang. 2015. Integrated index for drought assessment based on variable fuzzy set theory: A case study in the Yellow River basin, China. *Journal of Hydrology* 527: 608–618.
- Huang, S.Z., Q. Huang, J.X. Chang, and L. Xing. 2015. The response of agricultural drought to meteorological drought and the influencing factors: A case study in the Wei River Basin, China. *Agricultural Water Management* 159: 45–54.
- Huang, S.Z., Q. Huang, G.Y. Leng, and S.Y. Liu. 2016. A nonparametric multivariate standardized drought index for characterizing socioeconomic drought: A case study in the Heihe River Basin. *Journal of Hydrology* 542: 875–883.
- Jia, H.C., and H.D. Pan. 2016. Drought risk assessment in Yunnan Province of China based on wavelet analysis. *Advances in Meteorology* 2016(3): 1–10.
- Jiang, R.G., J.C. Xie, H.L. He, and J.W. Zhu. 2015. Use of four drought indices for evaluating drought characteristics under climate change in Shaanxi, China: 1951–2012. *Natural Hazards* 75(3): 2885–2903.
- Kendall, M.G. 1975. *Rank correlation methods*, 4th edn. London: Charles Griffin.
- Lei, J.R., Z.H. Liu, L. Bai, Z.S. Chen, J.H. Xu, and L.L. Wang. 2016. The regional features of precipitation variation trends over Sichuan in China by the ESMD method. *Mausam: Quarterly Journal of Meteorology, Hydrology and Geophysics* 67(4): 849–860.
- Li, B., H. Su, F. Chen, J.J. Wu, and J.W. Qi. 2013. The changing characteristics of drought in China from 1982 to 2005. *Natural Hazards* 68(2): 723–743.
- Li, H.B., X.F. Zhang, C.H. Hu, and Y.G. Wang. 2010. Analysis on annual sediment transport abruption of river basin based on B-G segmentation algorithm. *Journal of Hydraulic Engineering* 41(12): 1387–1392 (in Chinese).
- Li, H.F., J.L. Wang, and Z.J. Li. 2013. Application of ESMD method to air-sea flux investigation. *International Journal of Geosciences* 4(5): 8–11.
- Lin, Q.X., Z.Y. Wu, V.P. Singh, and G.H. Lu. 2017. Correlation between hydrological drought, climatic factors, reservoir operation, and vegetation cover in the Xijiang Basin, South China. *Journal of Hydrology* 549: 512–524.
- Liu, L., Y. Hong, C.N. Bednarczyk, and J. Hocker. 2012. Hydroclimatological drought analyses and projections using meteorological and hydrological drought indices: A case study in Blue River Basin, Oklahoma. *Water Resources Management* 26(10): 2761–2779.
- Liu, Y., L.L. Ren, Y. Hong, and S.H. Jiang. 2016. Sensitivity analysis of standardization procedures in drought indices to varied input data selections. *Journal of Hydrology* 538: 817–830.
- Liu, Z.P., Y.Q. Wang, M.G. Shao, X.X. Jia, and X.L. Li. 2016. Spatiotemporal analysis of multiscale drought characteristics across the Loess Plateau of China. *Journal of Hydrology* 534: 281–299.
- Mann, H.B. 1945. Nonparametric tests against trend. *Econometrica* 13(3): 245–259.
- Mallya, G., V. Mishra, D. Niyogi, and R.S. Govindaraju. 2016. Trends and variability of droughts over the Indian monsoon region. *Weather and Climate Extremes* 12: 43–68.
- Ming, B., Y.Q. Guo, H.B. Tao, G.Z. Liu, S.K. Li, and P. Wang. 2015. SPEIPM-based research on drought impact on maize yield in

- North China Plain. *Journal of Integrative Agriculture* 14(4): 660–669.
- Portela, M.M., J.F.D. Santos, A.T. Silva, J.B. Benitez, C. Frank, and J.M. Reichert. 2015. Drought analysis in southern Paraguay, Brazil and northern Argentina: Regionalization, occurrence rate and rainfall thresholds. *Hydrology Research* 46(5): 1–19.
- Qin, Y.H., B.F. Li, Z.S. Chen, Y.N. Chen, and L.S. Lian. 2017. Spatio-temporal variations of nonlinear trends of precipitation over an arid region of northwest China according to the extreme-point symmetric mode decomposition method. *International Journal of Climatology* 38(5): 2239–2249.
- Salami, A.W., A.A. Mohammed, Z.H. Abdulmalik, and O.K. Olanlokun. 2014. Trend analysis of hydro-meteorological variables using the Mann-Kendall trend test: Application to the Niger River and the Benue Sub-Basins in Nigeria. *International Journal of Technology* 5(2): 100–110.
- Sheffield, J., K.M. Andreadis, E.F. Wood, and D.P. Lettenmaier. 2009. Global and continental drought in the second half of the twentieth century: Severity-area-duration analysis and temporal variability of large-scale events. *Journal of Climate* 22(8): 1962–1981.
- Shen, X.M., X. Wu, X.M. Xie, Z.Z. Ma, and M.J. Yang. 2017. Spatiotemporal analysis of drought characteristics in Song-Liao River Basin in China. *Advances in Meteorology* 2017(6): 1–13 (in Chinese).
- Tong, S.Q., Q. Lai, J.Q. Zhang, Y.H. Bao, A. Lusi, Q.Y. Ma, X.Q. Li, and F. Zhang. 2018. Spatiotemporal drought variability on the Mongolian Plateau from 1980–2014 based on the SPEI-PM, intensity analysis and Hurst exponent. *Science of the Total Environment* 615: 1557–1565.
- Vicente-Serrano, S.M., S. Begueia, and J.I. Lopez-Moreno. 2010. A multiscalar drought index sensitive to global warming: The standardized precipitation evapotranspiration index. *Journal of Climate* 23(7): 1696–1718.
- Wang, J.L., and Z.J. Li. 2013. Extreme-point symmetric mode decomposition method for data analysis. *Advances in Adaptive Data Analysis* 5(3): Article 1350015.
- Wang, Z.L., J. Li, C.G. Lai, R.Y. Wang, X.H. Chen, and Y.Q. Lian. 2018. Drying tendency dominating the global grain production area. *Global Food Security* 16: 138–149.
- Wu J.F., X. Chen, L. Gao, H.X. Yao, Y. Chen, and M.B. Liu. 2016. Response of hydrological drought to meteorological drought under the influence of large reservoir. *Advances in Meteorology* 2016(4): 1–11.
- Yang, M., D. Yan, Y. Yu, and Z. Yang. 2016. SPEI-Based spatiotemporal analysis of drought in Haihe River Basin from 1961 to 2010. *Advances in Meteorology* 2016(1): 1–10.
- Yang, P., J. Xia, Y.Y. Zhang, C.S. Zhan, and Y.F. Qian. 2018. Comprehensive assessment of drought risk in the arid region of Northwest China based on the global palmer drought severity index gridded data. *Science of the Total Environment* 627: 951–962.
- Yao, N., Y. Li, T.J. Lei, and L.L. Peng. 2017. Drought evolution, severity and trends in mainland China over 1961–2013. *Science of the Total Environment* 616–617: 73–89.
- Yu, M.X., Q.F. Li, M.J. Hayes, M.D. Svoboda, and R.R. Heim. 2014. Are droughts becoming more frequent or severe in China based on the Standardized Precipitation Evapotranspiration Index: 1951–2010? *International Journal of Climatology* 34(3): 545–558.
- Zhang, Q., and Z.H. Hu. 2018. Assessment of drought during corn growing season in Northeast China. *Theoretical and Applied Climatology* 133(3–4): 1315–1321.
- Zhang, D.Q., L. Zhang, J. Yang, and G.L. Feng. 2010. The impact of temperature and precipitation variation on drought in China in last 50 years. *Acta Physica Sinica* 59(1): 655–663.
- Zhang, H.B., Q. Huang, Q. Zhang, L. Gu, K.Y. Chen, and Q.J. Yu. 2015. Changes in the long-term hydrological regimes and the impacts of human activities in the main Wei River, China. *International Association of Scientific Hydrology Bulletin* 61(6): 1054–1068.
- Zhang, Q., X.H. Gu, V.P. Singh, and M.Z. Xiao. 2014. Flood frequency analysis with consideration of hydrological alterations: Changing properties, causes and implications. *Journal of Hydrology* 519: 803–813.
- Zhong, F., X.L. Su, and J. Guo. 2017. Trends and multiple time scale characteristics of aridity index in Heihe River Basin. *Journal of Northwest A & F University (Natural Science Edition)* 45(9): 136–144 (in Chinese).
- Zhou, L., J.J. Wu, X.Y. Mo, H.K. Zhou, C.H. Diao, Q.F. Wang, Y.H. Chen, and F.Y. Zhang. 2017. Quantitative and detailed spatiotemporal patterns of drought in China during 2001–2013. *Science of the Total Environment* 589: 136–145.
- Zuo, D.P., S.Y. Cai, Z.X. Xu, F.L. Li, W.C. Sun, X.J. Yang, G.Y. Kan, and P. Liu. 2018. Spatiotemporal patterns of drought at various time scales in Shandong Province of Eastern China. *Theoretical and Applied Climatology* 131(1–2): 271–284.