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ORIGINAL PAPER

Multi-scale response of runoff to climate fluctuation in the headwater region of Kaidu River in Xinjiang of China

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Abstract Based on the hydrological and meteorological data in the headwater region of the Kaidu River during 1960–2009, the multi-scale characteristics of runoff variability were analyzed using the ensemble empirical mode decomposition method (EEMD), and the aim is to investigate the oscillation mode structure characteristics of runoff change and its response to climate fluctuation at different time scales. Results indicated that in the past 50 years, the overall runoff of Kaidu River in Xinjiang has showed a significant nonlinear upward trend, and its changes have obviously exhibited an inter-annual scale (quasi-3 and quasi-6-year) and inter-decadal scale (quasi-10 and quasi-25-year). Variance contribution rates of each component manifested that the inter-decadal change had been playing a more important role in the overall runoff change for Kaidu River, and the reconstructed inter-annual variation trend could describe the fluctuation state of the original runoff anomaly during the study period. The reconstructed inter-decadal variability effectively revealed that the runoff for Kaidu River changed over the years, namely the states of abundance and low water period appear alternately. In addition, we found that runoff has a positive correlation to precipitation and temperature at different time scales, but they are most significant and relevant at inter-decadal scale, indicating the inter-decadal scale is most suitable for investigating the responses of runoff dynamics to climate fluctuation. At the same time, the results also suggested that EEMD is an effective method to analyze the multi-scale characteristics of nonlinear and non-stationary signal.

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1 Introduction

In its latest report for 2013, the Intergovernmental Panel on Climate Change (IPCC) has noted that the average global temperature has increased by 0.85 °C (0.65–1.06 °C) and the annual average temperature from 2003 to 2012 increased by 0.78 °C relative to 1850–1900, a period of nearly 130 years (1880–2012), indicating that rapid global warming is an indisputable fact (IPCC 2013). Climate warming will lead to changes in the hydrological cycle and cause redistribution of water resources and water quantity changes in time and space, thereby affecting the development of ecological and socioeconomic environment (Zhang et al. 2004). Xinjiang, one of the main arid areas in Northwest China, belongs to the typical temperate continental arid climate. In the context of global warming, the climate has transformed from “warm and dry” to “warm and wet” since 1987 (Shi et al. 2007) and the temperature, precipitation, and soil moisture show an increasing trend (Li et al. 2011, 2012a, b; Wang et al. 2013; Jiang et al. 2009). Among them, the precipitation changes and changes in water resources are even more important for industrial and agricultural development in Xinjiang (Chen et al. 2011). Kaidu River, one of the rivers with the richest water in southern slope of Tianshan Mountain, is the main water source for ecological environment construction, agricultural irrigation, power generation, sewage, and groundwater recharge in Bayinguoleng Mongolian Autonomous Prefecture of Xinjiang and also is a source of natural regulating reservoir of Bosten Lake. Therefore, the study on hydrology and water resources cycle of Kaidu River as well as its response to climate change under the background of global warming has important practical significance and scientific value, which has been of great concern.

Hydro-climatic change detection is one of the core issues in hydro-climatic process research, which plays a crucial role in accurately estimating global and regional hydro-climatic change trends and understanding their complex mechanism (Xu et al. 2013; Xue et al. 2013). Currently, most researchers apply methods such as a moving average or polynomial, linear regression, empirical or spline function fitting, singular spectrum analysis (SSA), Mann-Kendall trend and jump detection, empirical orthogonal functions (EOF), wavelet analysis, and artificial neural network for the fitting of hydro-climatic change trends (Wei 2007; Li et al. Li et al. 2012a, b; Chen et al. 2013; Xu et al. 2013). In fact, the hydro-climatic process is a complex nonlinear system, and most of the long-term variations in many hydro-climatic factors, including runoff, precipitation, and temperature, exhibit nonlinear, non-stationary complex processes of change, accompanied by a variety of scales or periodic oscillations (Xu et al. 2010, 2013; Franzke 2014). Due to limitations in the conventional methods used, neither an accurate nor reasonable diagnosis is provided for the natural variability of hydro-climatic process in many hydro-climatic change research studies. To date, the understanding of the process of hydro-climatic change in its basic form remains a major problem. With the rapid development of signal detection technology, Wu and Huang (2009) have proposed a new time-series signal processing method: ensemble empirical mode decomposition (EEMD). This method is a new development of empirical mode decomposition (EMD) (Huang et al. 1998), which has stronger self-adaptability and local variation characteristics based on the signal. These attributes can effectively improve the “mode mixing” issue of EMD, making it suitable for non-stationary and nonlinear signal detection, and it can gradually separate the oscillations at different scales (intrinsic mode function—IMF) or the trend components from the original signal. EEMD is one of the latest methods to extract signal variation trends. Moreover, in recent years, the EEMD method has been gradually applied in the field of hydro-climatic change research, and some meaningful results have been achieved (Shao et al. 2011; Wu et al. 2011; Kuo et al. 2013; Qian and Zhou 2014; Ji et al. 2014). However, there are few literatures to explore the nonlinear process of annual runoff for inland river in arid areas, characteristics of inter-annual and inter-decadal variation as well as the general trend of hydro-climatic variation in the typical arid area of northwestern China from different time scales. Therefore, to study the multi-scale features of runoff variation trends for Kaidu River in Xinjiang of China, we propose the EEMD method to extract variation at different scales in the hydro-climatic signals from the hydro-climatic time sequence and to conduct multi-scale analysis on runoff changes and its response to climate factors in the past 50 years.

The aim of the present study is to explore the following issues: (1) the oscillation and variation of time scale that have characterized runoff changes for Kaidu River in the past 50 years in Xinjiang, in particular, the evolutionary characteristics of oscillation and variation at different scales; (2) the contributions of oscillations at different scales to runoff changes and their significance or insignificance; (3) the impact of the oscillation at each scale on the overall runoff change in different periods; and (4) the response of runoff to climate factors. It is to be hoped that our study can deepen the understanding of the hydro-climatic process in the continental drainage basins of arid areas in the context of global warming.

2 Study area and data

2.1 Study area

The Kaidu River, a main tributary that discharges into the downstream of the Tarim River, is situated at the north fringe of the Yanqi Basin on the south slope of the Tianshan Mountains in Xinjiang, China, and is enclosed between latitudes 42° 14′–43° 21′ N and longitudes 82° 58′–86° 55′ E (Fig. 1). The river starts from the Hargat Valley and the Jacsta Valley in the Sarming Mountain and ends in the Bosten Lake which is located in Bohu county of Xinjiang. The basin area of the Kaidu River above Dashankou is 18, 827 km^2, with the elevation of 1042–4796 m (Chen et al. 2013). As the small population size live in the area, the local environment is affected only by low grazing. The average annual precipitation is less than 500 mm and pan evaporation is more than 1100 mm. The annual average temperature is only −4.6 °C and the extreme minimum temperature is −48.1 °C. The snow cover days are as many as 139.3 days and the largest average snow depth is 12 cm (Xu et al. 2013). The runoff in the Kaidu River is characterized by the snow melting in spring, the rainfall/snowfall and the perennial glacier melting in summer (Chen and Chen 2014). The headwater region of the Kaidu River plays a crucial role in regulating water, reserving water, and maintaining water balance. It also plays an important role in protecting the Bosten Lake and its surrounding wetlands and maintaining the ecological balance and green corridor of the lower reaches of the Tarim River.

2.2 Data

The Dashankou hydrological station is the last station before the Kaidu River reaches the plain oases from the mountainous area (Fig. 1).The observed annual runoff data for the period of 1960–2009 in Dashankou were provided by the Xinjiang Tarim River Basin Management Bureau, so the data is

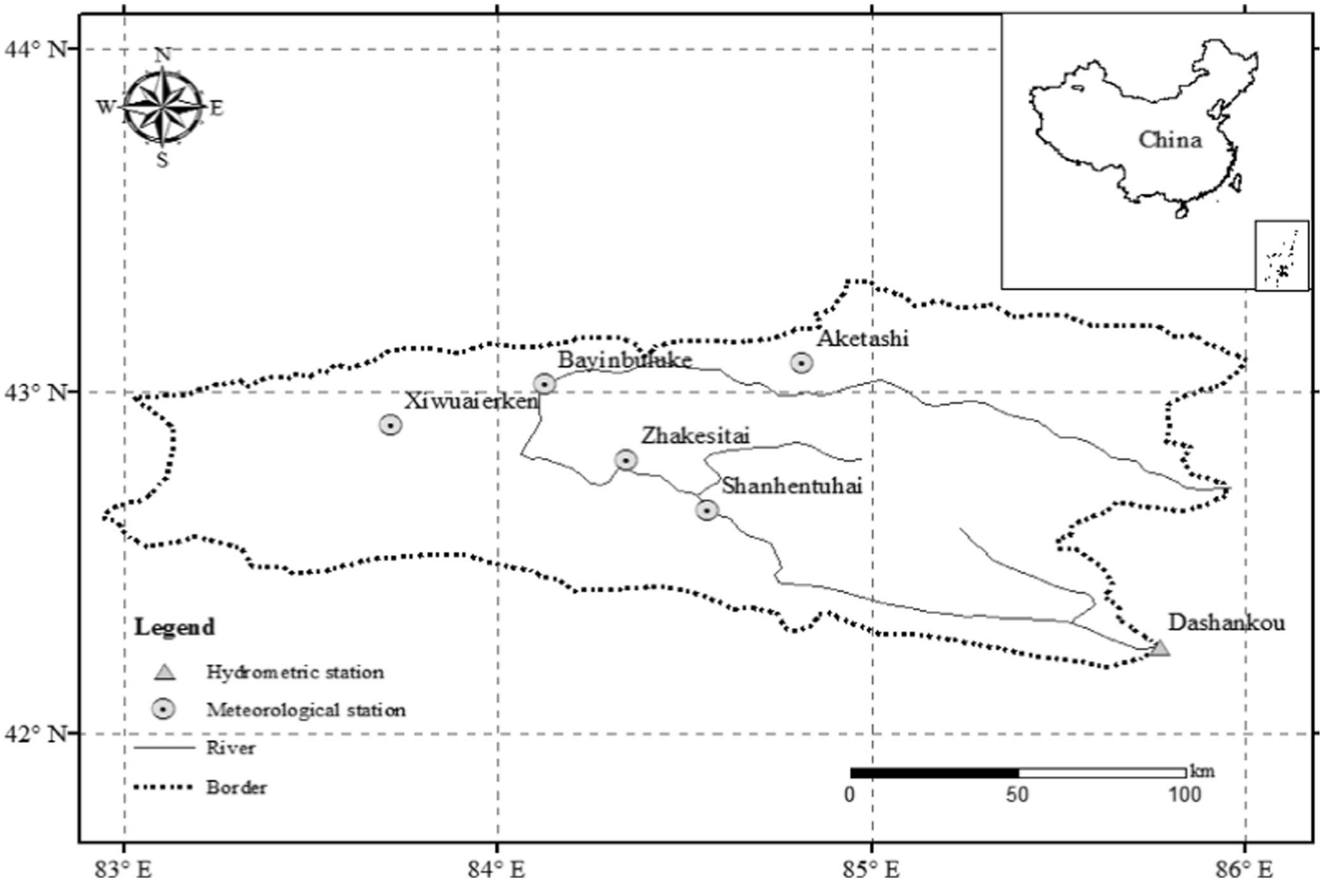

Fig. 1 Location of the headwater region of the Kaidu River and the distribution of meteorological and hydrological stations

reliable. There are five meteorological stations located in the study area (Fig. 1), so the precipitation and temperature data were available from five meteorological stations provided by the National Meteorological Information Center. The meteorological data had been proven to be unmistakable by means of the extreme value examination and time synchronization detection. Furthermore, missing data for individual years from some meteorological stations were interpolated by the ratio method, the uniformity inspection and revision of the climate data were conducted via RHTest software to eliminate data sequence breakpoints or adverse effects on the quality of the data resulting from migration of stations, instrument replacement, operating error of the observer, and other factors.

2.3 Methodology

To overcome the scale-mixing problem of the EMD method, a new noise-assisted data analysis method was proposed: the ensemble EMD (EEMD), which defines the true IMF components as the mean of an ensemble of trials, each consisting of a signal plus white noise of finite amplitude (Wu and Huang 2009). To better understand the EEMD method, the EMD method should be introduced first. The EMD method has been developed for nonlinear and non-stationary signal analysis, though only empirically. With the EMD method, a signal is decomposed into several intrinsic mode functions (IMFs), and after EMD processing, the frequencies of the IMFs are arranged in decreasing order (high to low), where the lowest frequency of the IMF components represents the overall trend of the original signal or the average of the time series data. Most importantly, each of these IMFs must satisfy two conditions: first, the number of extrema and the number of zero crossings must be equal or differ at most by one and second, at any point, the mean value of the envelope defined by the local maxima and local minima must be zero.

For the original signal x (t), first find out all the local maxima and minima, and then use cubic spline interpolation method to form the upper envelope u_1 (t) and the lower envelope u_2 (t); the local mean envelope m_1 (t) can be expressed as:

$$m_1(t) = \frac{1}{2}(u_1(t) + u_2(t)) \quad (1)$$

The first component h_1 (t) can be obtained by subtracting the local mean envelope m_1 (t) from the original signal x (t), with the mathematical expression as follows:

$$h_1(t) = x(t) - m_1(t) \quad (2)$$

If h_1 (t) does not satisfy the IMF conditions, regard it as the new x (t), and repeat the steps in formula (1) and (2) k times until h_{1k} (t) is obtained as an IMF.

$$h_{1k}(t) = h_{1(k-1)}(t) - m_{1k}(t) \tag{3}$$

Designate $C_1 = h_{1k}$ and select a stoppage criterion defined as follows:

$$SD = \sum_{t=0}^{T} \left[\frac{h_{1(k-1)}(t) - h_{1k}(t))}{h_{1(k-1)}(t)} \right]^2 \tag{4}$$

Here, the standard deviation (SD) is smaller than a predetermined value. If the above process is repeated too many times, the IMF will become a pure frequency modulation signal with constant amplitude in the actual operation, possibly resulting in loss of its actual meaning. According to Huang et al. (1998), SD (generally 0.2–0.3) can be adopted as the criterion to stop sifting process. In this study, we decomposed the data using EEMD with different SD values (i.e., 0.2 and 0.3), but found little differences between both. To facilitate the analysis, we only displayed the result of SD = 0.2. Once the first IMF component is determined, the residue r_1 (t) can also be obtained by separating C_1 from the rest of the data, i.e.,

$$r_1(t) = x(t) - C_1 \tag{5}$$

By taking the residue r_1 (t) as new data and repeating steps (1)–(5), a series of IMFs, namely, C_2, C_3, …, C_n can be obtained. The sifting process finally stops when the residue, r_n (t), becomes a monotonic function or a function with only one extremum from which no more IMF can be extracted. Finally, the original signal x (t) can be reconstructed by n IMFs (i.e., C_i (t)) and a residue r_n (t) as follows:

$$x(t) = \sum_{i=1}^{n} C_i(t) + r_n(t) \tag{6}$$

Although EMD has many merits, there is a shortcoming of mode mixing in EMD. Mode mixing is defined as a single IMF either consisting of signals of widely disparate scales or a signal of a similar scale residing in different IMF components (Wu and Huang 2009). Mode mixing not only causes serious aliasing in the time–frequency distribution but also makes the individual IMF devoid of physical meaning. To overcome the mode mixing problem, the ensemble empirical mode decomposition (EEMD) method has been recently developed for nonlinear and non-stationary signal analysis. The principle of EEMD is simple: adding white noise to the data, which distributes uniformly in the whole time–frequency space, the bits of signals of different scales can be automatically designed onto proper scales of reference established by the white noise. Although each individual trial may produce very noisy results, the noise in each trial is canceled out in the ensemble mean of enough trails (Wu and Huang 2009). Furthermore, the EEMD algorithm is straightforward and can be described as follows: first, add a white noise series to the original signal

$$x_i(t) = x(t) + n_i(t) \tag{7}$$

where x_i (t) is the new signal after adding ith white noise to the original signal data x (t), n_i (t) is the white noise. Then, decompose the signal with added white noise into IMFs using EMD according to the steps of (1)–(5) equation, the corresponding IMF components C_{ij} (t) and residue component r_i (t) of the decompositions were obtained. Finally, adopt the means of the ensemble corresponding to the IMFs of the decompositions as the final result, namely

$$C_j(t) = \frac{1}{N} \sum_{i=1}^{N} C_{ij}(t) \tag{8}$$

where C_j (t) is the final jth IMF component, N is the number of white noise series, C_{ij} (t) denotes the jth IMF from the added white noise trial. Wu and Huang (2009) noted that the amplitude size of the added noise exerts little influence on the decomposition results on the condition that it is limited, is not vanishingly small or very large, and can include all possibilities. Therefore, the application of the EEMD method does not rely on subjective involvement; it is an adaptive data analysis method.

In EEMD, the significance test can be carried out by means of white noise ensemble disturbance, to get each IMF credibility (Wu and Huang 2009; Huang and Shen 2005). To determine different scales of IMF components, we examined the more detailed distribution of the energy with respect to the period in the form of spectral function. The energy density of the kth IMF (E_k) can be defined as follows:

$$E_k = \frac{1}{N} \sum_{j=1}^{N} |I_k(j)|^2 \tag{9}$$

Where N is the length of the IMF component and I_k (j) denotes the kth IMF component (i.e., C_j). The white noise sequence is tested by the Monte Carlo method (Wu and Huang 2004). Next, before examining the periods of IMFs, we should list the properties of an IMF as follows: an IMF is any function having symmetric envelopes defined by the local maxima and minima separately and also having the same number of zero-crossings and extrema. Based on this definition, we can determine the mean period of the function by counting the number of peaks (local maxima) of the function (Wu and Huang 2004). The mean period of the kth IMF (T_k) can be defined as follows:

$$T_k = \frac{N}{\mathrm{NP}_k} \tag{10}$$

where N is the length of the IMF component, NP_k denotes the number of peaks for each IMF. Then, a simple equation that relates the averaged energy density $\bar{E}_k$ and the averaged period $\bar{T}_k$ is obtained:

$$\ln \overline{E}_k + \ln\left(\overline{T}_k\right)_a = 0 \tag{11}$$

As shown in the Fig. 4 with $\ln(\overline{T}_k)_\alpha$ as the x-axis and $\ln\bar{E}_k$ as the y-axis, the relation between the energy density and the averaged period can be expressed by a straight line whose slope is −1. The IMF component of the white noise series should be distributed on the line in theory; however, the actual application produces little deviation, so the confidence interval for the energy spectrum distribution of white noise is presented as follows (Xue et al. 2013):

$$\ln \overline{E}_k = -\ln\left\{\overline{T}_k\right\}_a \pm \alpha\sqrt{2/N}e^{\ln\left[\left(\overline{T}_i\right)\right]_{\alpha/2}} \tag{12}$$

In the formula, α is the significance level. At a given significance level (e.g., α = 0.05), the energy of IMFs through decomposition is located above the confidence curve, indicating the periodic oscillation has passed the significance test; on the contrary, it is considered less significant (Shao et al. 2011; Li et al. 2014).

In addition, to solve the overshooting and undershooting phenomenon of the impact of the boundary on the decomposition process, mirror-symmetric extension (Huang and Shen 2005; Xue et al. 2013) was used to address the EEMD decomposition boundary problem.

3 Results and discussion

3.1 Characteristics of runoff variation trend

As seen in Fig. 2, the runoff of Kaidu River has shown an overall increasing trend in nearly 50 years. There was a turning point of runoff in the mid-1990s, before which the runoff was relatively less and Kaidu River was relatively drier, while after which the runoff was more and the river water was more abundant. With respect to the time period, the runoff of Kaidu River was less during 1960–1995 and showed a gradual increase in the mid-1960s, 1970s, and 1980s, suggesting that the runoff in Kaidu River has experienced a rise in the dry period. The runoff in the Kaidu River was significantly more during the period 1996–2009 than ever before, during which the runoff showed a large inter-annual difference of up to $22.18 \times 10^8 m^3$, implying that an incidence of extreme hydrological events have increased significantly. Overall, the runoff variation during 1960–2009 showed a fluctuating upward trend, with the mean annual value of 35.10×10^8 m^3, and the ratio between the maximum (appeared in 2002) and minimum (appeared in 1986) annual runoff of 2.26:1. Referring to 5-year moving average of runoff anomaly (Fig. 2), it is clearly noted that the runoff change is not linear and shows a strong nonlinear variation trend. Furthermore, the stationary test of runoff series via ADF test (not shown) also indicates a non-stationary change in runoff. Therefore, a nonlinear method should be used to analyze the nonlinear and non-stationary changes of runoff in the Kaidu River.

The EEMD method has characteristics of self-adaptability and locality in time, which is suitable for the time–frequency analysis of nonlinear, non-stationary time series. Furthermore, compared with other methods, it can more efficiently extract trends and period information (Huang et al. 2009; Shao et al. 2011). Therefore, the EEMD method can be used to decompose time series of runoff anomaly in the Kaidu River during the period 1960–2009; for decompositions, the ensemble number is 100 and the added noise has amplitude that is 0.2 times the standard deviation of the corresponding data, and four IMF components (IMF1-4) and one trend component (RES) can be obtained (Fig. 3). Each IMF component reflects the fluctuation characteristics from high frequency (HF, less than 10-year period) to low frequency (LF, not less than 10-year period) at different time scales, and the final trend component represents the trend of the original data over time. Generally, each IMF component has a physical meaning, reflecting the oscillation of inherently different characteristic scales in the original series. The actual physical meaning contained in each IMF component at inherently different characteristic scales can be determined by the significance test and different confidence levels indicate the strength of the physical meaning. As shown in Fig. 4, the horizontal axis indicates the inherent scale characteristics of an IMF component, in which an IMF component closer to the left in Fig. 4 represents a higher frequency and a shorter period. The longitudinal axis indicates the energy spectral density of an IMF component, in which an IMF component closer to the top represents a higher energy and greater amplitude. Figure 4 clearly shows that IMF1 and IMF2 fall between 50 and 80 % confidence interval, indicating that they contain less information with actual physical meaning, while IMF3 and IMF4 fall above the 95 % confidence line, indicating that IMF3 and IMF4 are more significant components and contain more information with actual physical meaning. More or less physical meaning displayed in the significant test really means strength or weakness of the oscillation at a certain scale. In other words, more or less physical meaning indicates that whether the period of the examined oscillation (e.g., IMF1, IMF2, IMF3, or IMF4) is outstanding (Shao et al. 2011; Li et al. 2014). As seen in Fig. 4, the significance test shows that the runoff in Kaidu River during the study period has weak quasi-3-year (IMF1) and quasi-6-year (IMF2) periodic fluctuation at the inter-annual scale and significant quasi-10-year (IMF3) and quasi-25-year (IMF4) periodic variation at the inter-decadal scale.

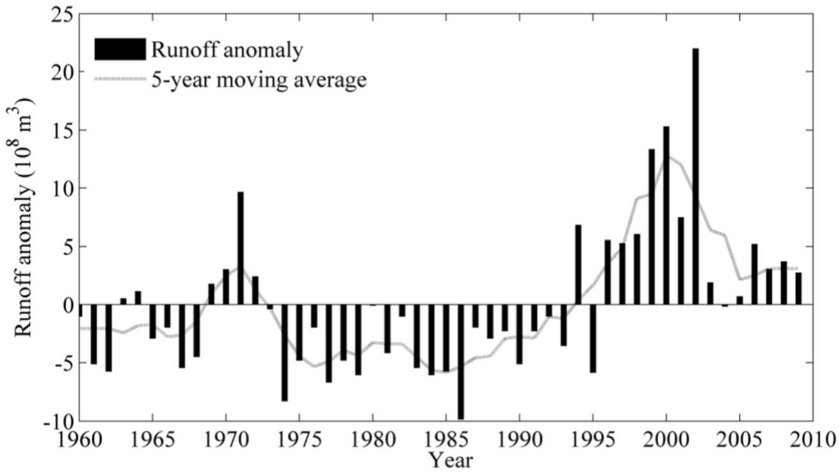

Fig. 2 Change in runoff anomaly during the period of 1960–2009

These IMF components include not only the periodic changes of hydrologic systems under external forcing but also the non-linear feedback of the hydrologic system. Shakure et al. (2014) analyzed the runoff change from Dashankou hydrological station in Kaidu River during the period 1956–2010 by wavelet analysis and found that the runoff change showed weak periodic variations of 6~10 at an inter-annual scale and significant cyclical changes of 16 and 27 years at an inter-decadal scale. These findings are not basically consistent with the results of EEMD decomposition, this may be due to the differences in study periods and study methods.

The impact of the signal fluctuation frequency and amplitude in each scale on the general characteristics of the available original data can be expressed as the variance contribution rate. Table 1 shows the variance contribution rate of each component for the runoff anomaly. It is noted that although IMF1 and IMF2 are weak periods, they are also involved in the calculation of the variance contribution rate to maintaining the total energy of the signal. When connecting Fig. 3 and Table 1, it can be seen that the largest contribution rate of the quasi-3-year cycle (IMF1) reaches 25.36 %, the oscillation signal is very clear, showing a decreasing–increasing–decreasing trend of runoff amplitude, and the runoff amplitudes in the late 1960s and early 1970s, from the middle and late 1990s to 2005, were significantly higher than other periods. The variance contribution of quasi-6-year cycle (IMF2) is approximately 15.51 %, basically reflecting the runoff amplitude from the 1960s to the mid-1970s was larger than the remaining period. The variance contribution of quasi-10-year cycle (IMF3) is 21.09 %, its amplitude from the mid-1970s to the mid-1990s was relatively smaller, and the runoff of Kaidu River displayed in a state of above normal in the late 1960s to the early 1970s, the late 1990s to 2005 at this time scale. The variance contribution of quasi-25 years (IMF4) is 20.42 %, and the runoff of Kaidu River displayed in a state of below and above normal level during 1970–1995 and

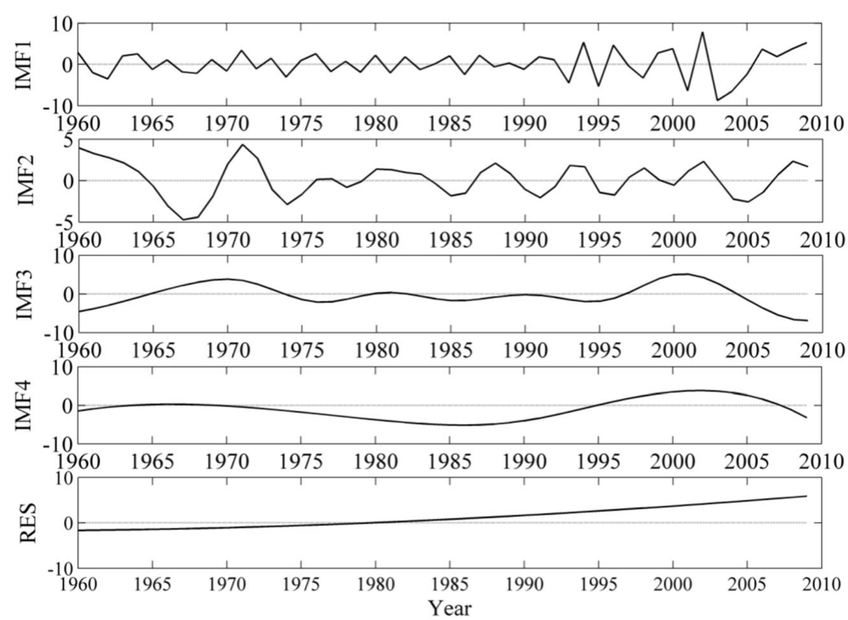

Fig. 3 The IMFs and trend component of runoff anomaly during the period 1960–2009

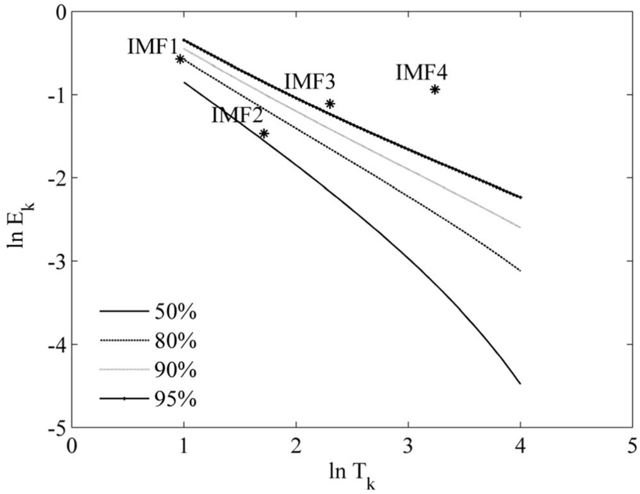

Fig. 4 Significance test for the IMFs of runoff anomaly during the period 1960–2009

1996–2007, respectively, at this time scale. The variance contribution of trend component (RES) can be up to 17.62 %, and the runoff of Kaidu River showed an approximately linear but actually a significant increasing nonlinear trend during 1960–2009.

Table 1 shows the variance contribution rate of each IMF component and also indicates that inter-decadal oscillations are stronger than inter-annual oscillations in runoff variation. Figure 5 shows the inter-annual and inter-decadal runoff variations in comparison with the original runoff anomaly series, in which the inter-annual runoff is obtained by intrinsic mode functions IMF1 and IMF2, which represent the inter-annual runoff variation plus trend component, while the inter-decadal runoff is obtained by intrinsic mode functions IMF3 and IMF4, which are representatives of the inter-decadal runoff variation plus trend component. It can be determined that the reconstructed inter-annual variation trend, which is basically consistent with the variation trend of original runoff anomaly series, can portray the fluctuations of the original runoff anomaly series in the study period, illustrating the inter-annual oscillations playing an important role in the overall runoff variation of Kaidu River. However, the change process of later annual runoff anomaly series portrayed by the reconstructed inter-annual runoff variation is not very satisfactory, which may be related to small-scale oscillation (i.e., HF) contained with more outside noise of system. The reconstructed inter-decadal variability effectively revealed that the runoff for Kaidu River changed over the years, namely the states of abundance and low water period appear alternately. The inter-decadal change is an essentially long and complex process of runoff change obtained by superimposing large-scale oscillations at an overall upward hydrological trend, and it can be found the runoff of Kaidu River fluctuated in the form of alternating positive and negative phase throughout the study period. From the view of inter-decadal fluctuations, the runoff variation of Kaidu River may change in a significant reduction stage in future. Compared to the original runoff anomaly series trend, the trend component through EEMD decomposition can fully reflect the overall upward trend of the average annual runoff variation in Kaidu River from 1960 to 2009.

Table 1 Contribution rates of EEMD decomposition for runoff anomaly

IMF components	IMF1	IMF2	IMF3	IMF4	RES
Period/year	3	6	10	25	
Contribution/%	25.36	15.51	21.09	20.42	17.62

3.2 The response of runoff variation to climate factors

In the context of global change, the annual runoff variations of Kaidu River are mainly affected by local climatic factors such as precipitation and temperature (Xu et al. 2008, 2013). It can be found through EEMD decomposition of precipitation in the same period as Kaidu River runoff, the precipitation in the river basin shows an overall upward trend and its changes have clearly exhibited relatively stable quasi-periodicity. As seen in Fig. 6a, the significance test for the IMFs of precipitation anomaly indicates that the precipitation variation has weak quasi-3-year (IMF1) and quasi-7-year (IMF2) periods at inter-annual scale and unobvious quasi-10 years (IMF3), and the strongest quasi-25 years (IMF4) periods at inter-decadal scale. Compared with the process of precipitation changes in the same period, the runoff variation of Kaidu River shows similar inter-annual scale and the same inter-decadal scale characteristics, and has consistency in variation trend. Similarly, it can be found through multi-scale decomposition of annual average temperatures during 1960–2009, the temperature variation in the basin shows an overall upward trend, and there are weak quasi-3-year and quasi-6-year periodic changes in its inter-annual scale and unobvious quasi-10-year, and the significant quasi-50-year periods in its inter-decadal scale (Fig. 6b). It can be seen, the annual average temperature variation in the river basin has same inter-annual scale characteristics to the annual runoff variation in the same period, but there are some differences at inter-decadal scale.

By contrast with the precipitation and temperature trend components (Fig. 7), the runoff variation of Kaidu River and its influencing factors have consistency in the variation trend but there are differences in the variation time points, combined with Figs. 5 and 7, the runoff of Kaidu River turned from negative to positive phase in the late 1970s and early 1980s, while the turning points of precipitation and temperature occurred in the middle and late 1980s, indicating the runoff variation of Kaidu River response to the regional climate

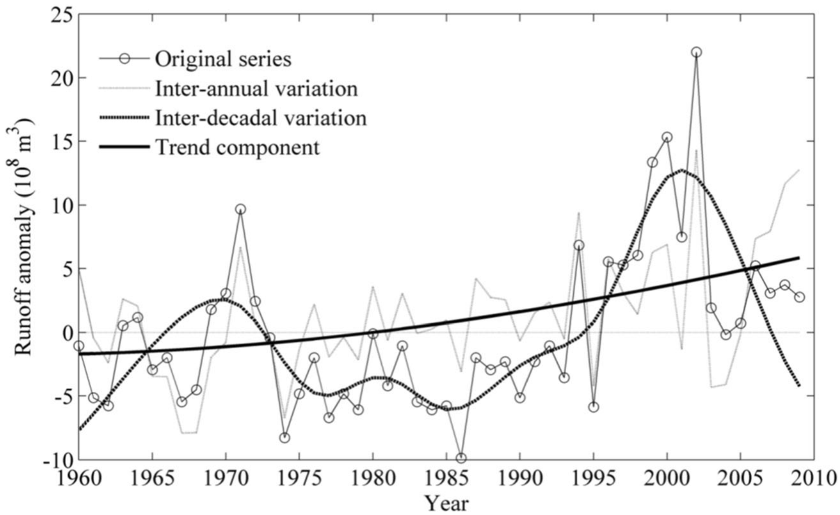

Fig. 5 Inter-annual and inter-decadal variations of runoff and their comparisons with runoff anomaly

change to some extent, but the variation time points are not fully synchronized.

To further analyze the correlation between runoff and precipitation and temperature, we reconstructed inter-annual and inter-decadal precipitation and temperature variations in comparison with the original precipitation and temperature anomaly series (not shown), in which the inter-annual precipitation/temperature is obtained by intrinsic mode functions IMF1 and IMF2, which represent the inter-annual precipitation/temperature variation plus trend component, while the inter-decadal precipitation/temperature is obtained by intrinsic mode functions IMF3 and IMF4, which are representatives of the inter-decadal precipitation/temperature variation plus trend component. Through the multi-scale correlation analysis of annual runoff, annual precipitation, and annual average temperature in Kaidu River, we find that runoff has a positive correlation to precipitation and temperature at different time scales (Table 2), but they are most significant and relevant at inter-decadal scale, indicating the inter-decadal scale is most suitable for investigating the responses of runoff dynamics to climate fluctuation. Furthermore, we find that the higher correlation between runoff and climate factors is precipitation, followed by temperature at both the inter-annual and inter-decadal scales, but the modulation effects of temperature on runoff are stronger than that of precipitation at both inter-annual vs. inter-decadal and inter-decadal vs. inter-annual scales. In addition, although there are differences in the length and strength of the periods among the precipitation, temperature, and runoff changes, the positive correlation between runoff, precipitation and temperature is still significant except for inter-annual precipitation vs. inter-decadal runoff, suggesting that the precipitation and temperature were both the main causes of runoff variation in Kaidu River. Furthermore, there are many other factors affecting the runoff, such as the varied topography, vegetation cover, and construction of water conservancy project (Chen et al. 2013; Li et al. 2013). Obviously, it is necessary to deeply explore mechanisms of runoff change with comprehensive consideration of various factors in future study.

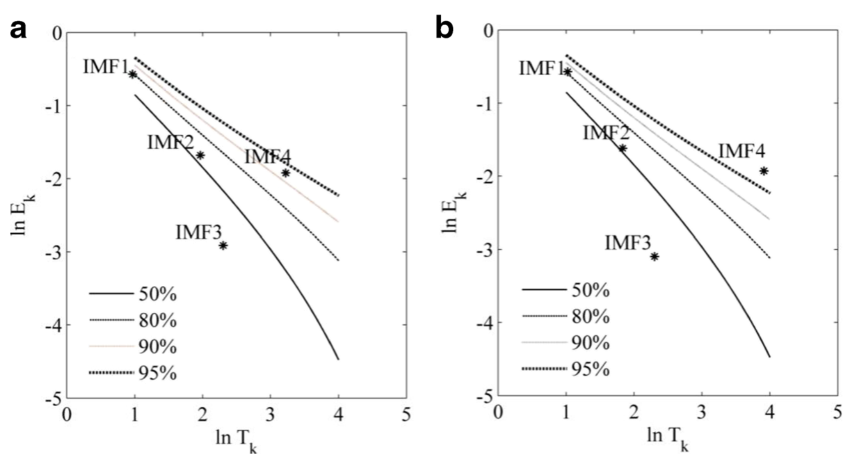

Fig. 6 Significance tests for the IMFs of precipitation anomaly (**a**) and temperature anomaly (**b**) during the period 1960–2009

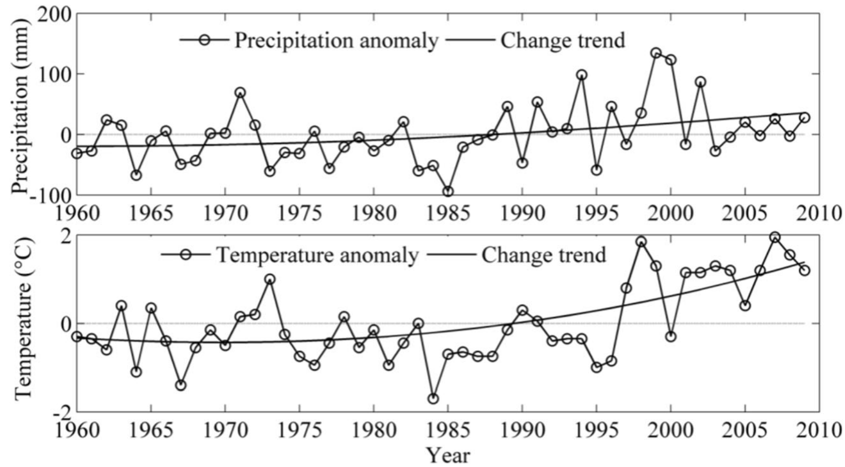

Fig. 7 The precipitation and temperature anomaly and their change trends during the period 1960–2009

4 Conclusions

EEMD is one of the signal analysis methods applicable to nonlinear and non-stationary series, and it has been proven to be a powerful tool in data analysis. When the EEMD is applied to the time series of hydro-climatic factors, the intrinsic time scales of hydro-climatic change can be extracted, it is helpful to identify hydrological and climatic change trends. In this study, based on the hydrological and meteorological data in the Kaidu River Basin during 1960–2009, the multi-scale response of runoff to climate fluctuation were analyzed using EEMD, the main findings are as follows:

1. In the past 50 years, the overall runoff of Kaidu River exhibited a significant nonlinear upward trend, and its changes obviously exhibited an inter-annual scale (quasi-3 years and quasi-6 years) and inter-decadal scale (quasi-10 years and quasi-25 years). In the four quasi-periodic components, quasi-3-year (IMF1) and quasi-6-year (IMF2) periodic fluctuation fall between 50 and 80 % confidence interval, indicating they are weak periods. Quasi-10-year (IMF3) and quasi-25-year (IMF4) periodic fluctuation fall above 95 % confidence line, suggesting that IMF3 and IMF4 are significant periods (i.e., main periods). The variance contribution rate of IMF1 was largest, reaching 25.36 %, the contribution of IMF2 was smallest, reaching 15.51 %, the variance contribution rates of IMF3 and IMF4 were relatively larger, with values of 21.01 and 20.42 % respectively, which implied that the inter-decadal change had been playing a more important role in the overall runoff change for Kaidu River.
2. The trend component through EEMD decomposition revealed that the runoff variation of Kaidu River during 1960–2009 showed an approximately linear but actually nonlinear evolution process and the average annual runoff had increased significantly since the early 1980s. The reconstructed inter-annual variation trend, which was basically consistent with the variation trend of original runoff anomaly series, can portray the fluctuations of the original runoff anomaly series in the study period, illustrating the inter-annual oscillations playing an important role in the overall runoff variation of Kaidu River. The reconstructed inter-decadal variability effectively revealed that the runoff for Kaidu River changed over the years, namely the state of abundance and low water period appear alternately. The inter-decadal change was an essentially long and complex process of runoff change obtained by superimposing large-scale oscillations at an overall upward hydrological trend, and it could be found the runoff of Kaidu River fluctuated in the form of alternating positive and negative phase throughout the study period.
3. Compared with the process of precipitation changes in the same period, the runoff variation of Kaidu River showed similar inter-annual scale and the same inter-decadal scale characteristics, and had consistency in variation trend. Compared with the process of temperature changes in the same period, both of them showed same inter-annual

Table 2 Correlations between runoff and climate factors during the period 1960–2009

Time scale	Precipitation vs. runoff	Temperature vs. runoff
Inter-annual scale	0.666**	0.416**
Inter-annual vs. inter-decadal scale	0.205	0.441**
Inter-decadal vs. inter-annual scale	0.279*	0.438**
Inter-decadal scale	0.822**	0.617**

**correlation is significant at the 0.01 level (two-tailed); *correlation is significant at the 0.05 level (two-tailed) scale characteristics but exhibited some differences in the inter-decadal scale, indicating the runoff variation of Kaidu River can better respond to precipitation. In addition, we found that runoff has a positive correlation to precipitation and temperature at different time scales, but they are most significant and relevant at inter-decadal scale, indicating the inter-decadal scale is most suitable for investigating the responses of runoff dynamics to climate fluctuation.

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