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The regional features of temperature variation trends over Xinjiang in China by the ensemble empirical mode decomposition method

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ABSTRACT: Based on a temperature anomaly time series from 16 international exchange stations in Xinjiang from 1957 to 2012, the multi-scale characteristics of temperature variability were analysed using the ensemble empirical mode decomposition (EEMD) method. Regional differences in variation trends and change-points were also preliminarily discussed. The results indicated that in the past 50+ years, the overall temperature in Xinjiang has exhibited a significant nonlinear upward trend, and its changes have clearly exhibited an inter-annual scale (quasi-3 and quasi-6-year) and inter-decadal scale (quasi-10 and quasi-30-year). The variance contribution rates of each component demonstrated that the inter-annual change had a strong influence on the overall temperature change in Xinjiang, and the reconstructed inter-annual variation trend could describe the fluctuation state of the original temperature anomaly during the study period. The reconstructed inter-decadal variability revealed that the climate mode in Xinjiang had a significant transformation before and after 1995, namely the temperature anomaly shift from a negative phase to a positive one. Furthermore, there were regional differences in the nonlinear changes and change-points of temperature. At the same time, the results also suggested that the EEMD method can effectively reveal variations in long-term temperature sequences at different time scales and can be used for the complex diagnosis of nonlinear and non-stationary signal changes.

KEY WORDS Xinjiang; temperature anomaly; ensemble empirical mode decomposition; intrinsic mode function; regional difference

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1. Introduction

With the growing effect of global warming on the environment and socio-economic development, climate change research has attracted broad attention from national government departments and the public (Intergovernmental Panel on Climate Change (IPCC), 2007). In its latest report for 2013, the 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). In the context of global warming, the temperature variation trend in China has also been on the rise, but the warming process is volatile with significant differences in time and space (Sun and Lin, 2007). Domestic scholars have conducted many research studies on temperature variation and its possible causes in China spanning periods from 50 years to over a century (Wang *et al.*, 1998; Ren *et al.*, 2005; Zhao *et al.*, 2005; Li *et al.*, 2010; Huang *et al.*, 2011). While many useful conclusions have been drawn, the findings differ in each study, and it has become indisputable that the temperature in China has changed significantly, with clear regional features. Xinjiang, one of the main arid areas in Northwest China, is characterised by a typical temperate continental arid climate, and its temperature has risen year-by-year in the context of global warming. Owing to its natural geographic feature of ‘three mountains sandwiched between two basins’, the temperature variation in Xinjiang is unique, and its temperature increase has been synchronous with global and national warming but is significantly higher in magnitude than global and national warming (Li *et al.*, 2006, 2012; Fan *et al.*, 2011). Furthermore, the temperature variation also exhibits significant seasonal and regional differences (Li *et al.*, 2011, 2013; Xu *et al.*, 2013). Therefore, the study of temperature variation in Xinjiang has important practical significance and scientific value in regards to global warming, which has been of great concern.

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Climate change detection is one of the core issues in climate change research, which plays a crucial role in accurately estimating global and regional climate change trends and understanding their causes (Sun and Lin, 2007). Currently, most researchers apply methods such as a moving average or polynomial, linear regression, empirical or spline function fitting, singular spectrum analysis (SSA), empirical orthogonal functions (EOF) and rotated empirical orthogonal functions (REOF) for the fitting of climate change trends (Wei, 2007; Wu and Wu, 2010). In fact, the climate system is a complex nonlinear system, and most of the long-term variations in many climatic factors, including temperature, exhibit nonlinear, non-stationary complex processes of change, accompanied by a variety of scales or periodic oscillations (Wu *et al.*, 2007; Xu *et al.*, 2013; Xue *et al.*, 2013; Franzke, 2014). Because of limitations in the conventional methods used, neither an accurate nor reasonable diagnosis is provided for the natural variability of climate change in many climate change research studies. To date, the understanding of the process of climate 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: the ensemble empirical mode decomposition (EEMD). This method is a new development of empirical mode decomposition (EMD), 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 (Wu and Huang, 2009). EEMD is one of the latest methods to extract signal variation trends. Compared with other methods, it can more efficiently extract trends and periodic information (Huang *et al.*, 2009; Shao *et al.*, 2011; Li *et al.*, 2012). Moreover, in recent years, the EEMD method has been gradually applied in the field of climate change research, and some meaningful results have been achieved (Wu *et al.*, 2011; Kuo *et al.*, 2013; Ji *et al.*, 2014; Qian and Zhou, 2014).

The aim of this study is to explore the following issues: (1) the oscillation and variation of time scale that have characterised temperature changes 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 temperature changes and their significance or insignificance; (3) the effect of the oscillation at each scale on the overall climate change in different periods; and (4) the relationship between temperature changes and regional differences. To study the regional features of temperature variation trends over Xinjiang in China, we propose the EEMD method to extract variation at different scales in the climatic signals from the climatic time sequence and to conduct multi-scale analysis on temperature changes in the past 50+ years in Xinjiang in the context of global warming.

2. Materials and methods

2.1. Study area and data processing

Located in the northwestern part of China, Xinjiang is a typical semiarid to arid area. It extends between 73°40′–96°23′E and 34°25′–48°10′N and covers an area of $166.04 \times 104\,\mathrm{km}^2$ (Xu *et al.*, 2013). The study area is far from the sea, located in the hinterland of Eurasia, and it belongs to a temperate and warm temperate arid region. With its typical continental climate, abundant sunshine, large temperature change magnitudes, scarce rain and snow, dry climate and intense evaporation, it is one of the most severely arid areas in the world. Owing to the lack of a dense network of international exchange stations in Xinjiang, only 16 international exchange stations with the most continuous temperature records were selected to cover the entire study area. In addition, to conduct comparative analysis with the temperature variation trends of the areas surrounding Xinjiang, temperature data from six representative meteorological stations with more complete time series within a buffer area of 150 km outward from the Xinjiang border were selected. The annual average China meteorological station temperature data from 1957 to 2012 were provided by China Meteorological Data Sharing Service System (http://cdc.cma.gov.cn/), while data from foreign meteorological stations were provided by the National Oceanic and Atmospheric Administration (http://www.climate.gov/). To determine which data have higher quality, the data have been subjected to extremum, time consistency and other tests. Furthermore, missing data for individual years from some meteorological stations were interpolated by the ratio method; the uniformity inspection and revision of the temperature 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 errors of the observer and other factors. The geographical distribution of the selected meteorological stations in Xinjiang and the surrounding areas is shown in Figure 1.

2.2. Methodology

To overcome the scale-mixing problem of the EMD method, a new noise-assisted data analysis method was proposed: the 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 allow better understand of the EEMD method, the EMD method will 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 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

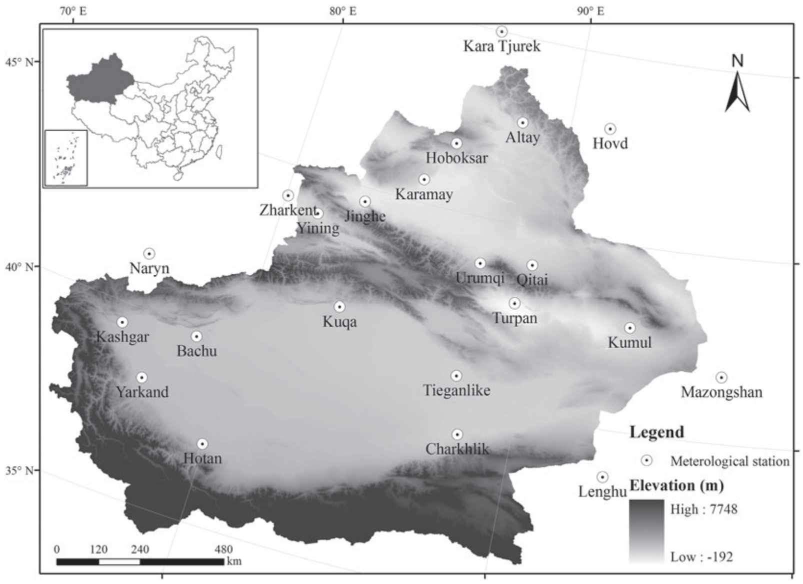

Figure 1. A map of Xinjiang and the distribution of meteorological stations.

equal or differ at most by one; second, at any point, the mean value of the envelope defined by the local maxima and local minima must be zero.

With the above definition for IMF, any original signal expressible as $x(t)$ can be decomposed in the following steps:

First, identify the local maxima and minima of the original data $x(t)$, then connect by a cubic spline line to produce the upper and lower envelopes, respectively, to obtain the local mean value of the corresponding data point $m_1(t)$, and define the difference between $x(t)$ and $m_1(t)$ as the first component $h_1(t)$ according to the following equations:

$$m_1(t) = \frac{1}{2}\left(u_1(t) + u_2(t)\right) \tag{1}$$

$$h_1(t) = x(t) - m(t) \tag{2}$$

If $h_1(t)$ does not meet 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. Therefore, SD (generally 0.2–0.3) should be used as a criterion to stop the sifting process; when the SD reaches a certain threshold, sifting should stop. Once the first IMF component is determined, the residue $r_1(t)$ can also be obtained by separating $C1$ 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 $C_2, C_3 \ldots$ can be obtained. The sifting process is stopped until $r_i(t)$ becomes a monotonic function or $|r_i(t)|$ is very small. Finally, the original signal can be reconstructed as follows:

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

Although EMD has many merits, mode mixing also has its shortcomings. Mode mixing not only causes serious aliasing in the time–frequency distribution but also causes the physical meaning of individual IMFs to be unclear. To overcome the shortcomings of the mode mixing problem in EMD, EEMD method has been recently developed for nonlinear and non-stationary signal analysis. The principle of EEMD is simple, which includes adding white noise to the data to be uniformly distributed over the entire time–frequency space, where the bits of signals of different scales can be automatically designated to proper scales of reference established by the white noise. In addition, the EEMD algorithm is straightforward and can be described as follows: (1) add a white noise series to the original signal; (2) decompose the signal with added white noise into IMFs using EMD; (3) repeat steps (1) and (2) with a different white noise series each time; and (4) obtain the corresponding IMF components of the decompositions and adopt the means of the ensemble corresponding to the IMFs of the decompositions as the final result. 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.

Because the data almost always contain noise, a natural question is whether a component (an IMF for EEMD) contains a true signal or is only a component of noise. To answer this question, a significance test based on the Monte-Carlo method was used (Wu and Huang, 2004). Next, the real IMF components were selected by examining 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 can be defined as follows:

$$E_k = \frac{1}{N}\sum_{j=1}^{N}\left|I_k(j)\right|^2 \tag{7}$$

where N is the length of the IMF component and $I_k(j)$ denotes the kth IMF component. The white noise sequence is tested by the Monte-Carlo method; then, a simple equation that relates the energy density E_k and the averaged period T_k is obtained:

$$\ln \overline{E}_k + \ln\left\{\overline{T}_k\right\}_\alpha = 0 \tag{8}$$

As shown in the Figure 4 with $\ln\left\{\overline{T}_k\right\}_\alpha$ as the x axis and $\ln \overline{E}_k$ as the y axis, then 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:

$$\ln \overline{E}_k = -\ln\left\{\overline{T}_k\right\}_\alpha \pm \alpha\sqrt{2/N}\,\mathrm{e}^{\ln\left(\left\{\overline{T}_k\right\}_{\alpha/2}\right)} \tag{9}$$

In the formula, α is the significance level.

In this article, based on temperature anomaly time series from 16 international exchange stations in Xinjiang from 1957 to 2012, the multi-scale characteristics of temperature variability were analysed using the EEMD method. For decompositions, the ensemble number was 100, the ratio of the SD of the added noise and that of the signal to be analysed was 0.2. Furthermore, a statistical significance test of IMFs decomposed by the EEMD method was conducted. In addition, to solve the overshooting and undershooting phenomenon of the effect of the boundary on the decomposition process, mirror-symmetric extension (Huang and Shen, 2005; Xue *et al.*, 2013) was used to address the EEMD boundary problem.

3. Results and discussion

3.1. Characteristics of temperature variation trend

As seen in Figure 2, the temperature in Xinjiang over nearly 50 years presents an overall increasing trend. A turning point appeared in the late 1980s and early 1990s, before which the temperature was lower and after which the temperature was higher. With respect to the time

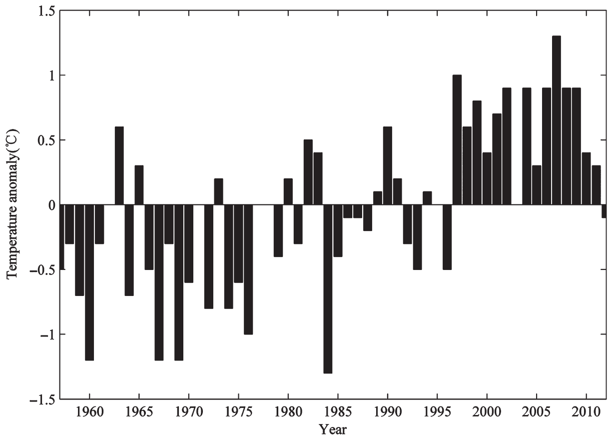

Figure 2. Change in the temperature anomaly from 1957 to 2012 in Xinjiang.

period, the temperature in Xinjiang was lower during 1957 to 1988 and showed a gradual increase in the 1960s, 1970s and the early 1980s, suggesting that the temperature in Xinjiang has also experienced a rise in the low-temperature period. The temperature in Xinjiang was, overall, higher in the 1990s, with large differences of up to 2.6 °C in temperature each year during which an incidence of extreme temperature would occur. The overall temperature remained higher in the first 10 years of the 21st century, but it was significantly higher than that of the later period, and extreme temperature events have increased significantly. Figure 2 shows that the temperature change is not linear and shows a strong nonlinear variation trend; the Xinjiang temperature change in the stationary test also shows non-stationary results. Therefore, a nonlinear method should be used to analyse the nonlinear and non-stationary changes of Xinjiang temperatures.

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. Therefore, the EEMD method can be used to decompose time series of temperature anomalies in Xinjiang during 1957 to 2012, and four IMF components (IMF1-4) and one trend component (RES) can be obtained (Figure 3). Each IMF component reflects the fluctuation characteristics from high frequency to low frequency 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 Figure 4, the horizontal axis indicates the inherent scale characteristics (cycle) of an IMF component, in which an IMF component closer to the left in Figure 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

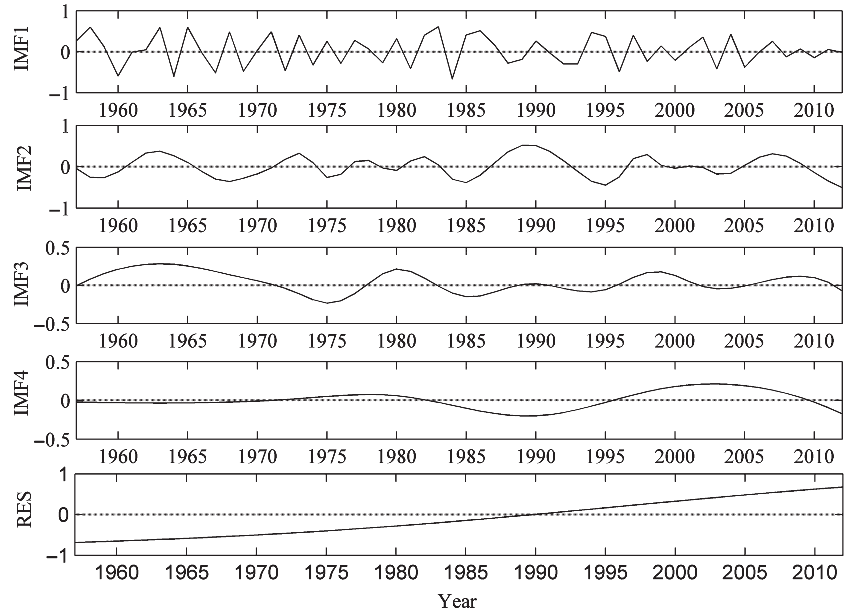

Figure 3. The IMF and trend components of the temperature anomaly from 1957 to 2012 in Xinjiang.

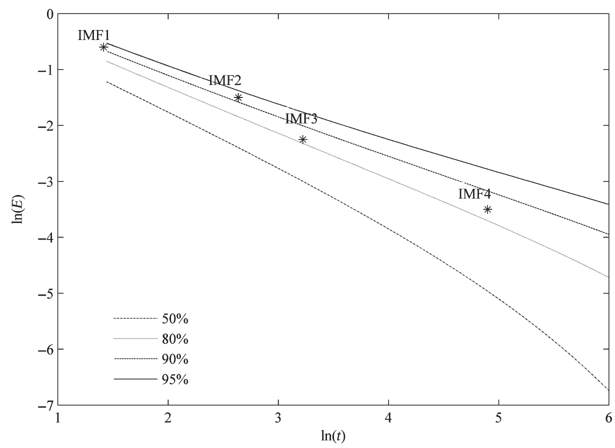

Figure 4. Significance test for the IMF of the temperature anomaly from 1957 to 2012 in Xinjiang.

and greater amplitude. Figure 4 clearly shows that IMF1 and IMF2 fall between 90 and 95% confidence interval, indicating that IMF1 and IMF2 are the more significant components and contain more information with actual physical meaning, while IMF3 and IMF4 fall between 80 and 90% confidence interval, indicating that they contain less information with actual physical meaning. As seen in Figures 3 and 4, the temperature changes from 1957 to 2012 in Xinjiang show relatively stable quasi periodicity; the temperature in Xinjiang during the study period has quasi-3-year (IMF1) and quasi-6-year (IMF2) climate variability at the inter-annual scale and quasi-10-year (IMF3) and quasi-30-year (IMF4) climate variability at the decadal scale. These IMF components include not only the periodic changes of climatic systems under external forcing but also the nonlinear feedback of the climatic system. Dai *et al.* (2007) analysed the temperature change from 12 meteorological stations in Xinjiang during the period from 1951 to 2005 by wavelet power spectrum and found that the temperature change showed significant periodic variations of 3 and 6 years at an inter-annual scale and weak cyclical changes of 11 and 16 years at an inter-decadal scale. This result is mostly consistent with the inter-annual scale characteristics determined in this study through the application of the EEMD method, with some differences on the inter-decadal scale that may be due to the differences in stations and study periods. Long-term observational data of the time series will be required to verify which results are more accurate. It is commonly known that the wavelet transform has been widely used in climate change detection (Gong *et al.*, 2005; Xu *et al.*, 2011). Therefore, we selected different wavelet bases and decomposition levels for the multi-scale decomposition of temperature anomalies in Xinjiang and found that if different wavelet bases and decomposition levels are selected, the decomposition results exhibit apparent differences (not shown), indicating that the wavelet transform is not adaptive. Compared with the wavelet transform, the EEMD method has stronger flexibility and adaptability, the decomposition process is simpler, and each component can clearly depict the signal variation characteristics at different time scales.

The effect of the signal fluctuation frequency and amplitude in each scale on the general characteristics of the available raw data can be expressed as the variance contribution rate. Table 1 shows the variance contribution rate

Table 1. Contribution rates of EEMD decomposition for temperature anomaly.

IMF components	IMF1	IMF2	IMF3	IMF4	RES
Period (year)	3	6	10	30	
Contribution (%)	28.29	19.61	10.11	8.58	33.40

of each component for the temperature anomaly. It is noted that although there is less information with actual physical meaning included in IMF3 and IMF4, they are also involved in the calculation of the variance contribution rate in maintaining the total energy of the signal. When connecting Figure 3 and Table 1, the contribution of IMF1 towards temperature variance of the quasi-3-year is greatest, reaching 28.29%. The amplitude of the temperature strongly oscillates from a decrease–increase–decrease trend and is significantly higher in the late 1960s, the late 1970s, early 1980s and 1990s than those of other time periods. IMF2 contributes to approximately 19.61% of the temperature variance of the quasi-6-year cycle, indicating higher temperatures in the late 1980s and early 1990s; IMF3 contributes 10.11% of the quasi-10-year temperature variance, indicating a relatively larger amplitude in the 1960s to 1970s; IMF4 contributes to 8.58% of the temperature variance of the quasi-30-year cycle, indicating that the temperature amplitude increases and the instability of variation increases on this time scale. The trend components contribute up to 33.40% of the variance, indicating that the overall average annual temperature in Xinjiang during 1957 to 2012 has a nonlinear rise with greater temperature increases from the late 1980s, which is consistent with the time of northwest climate transition defined by Shi *et al.* (2002). Furthermore, studies have shown that with global temperature changes over nearly 100 years, Europe and China have also experienced a nonlinear complex process of change (Sun and Lin, 2007; Wang and Li, 2011; Ji *et al.*, 2014), which indicates that the nonlinear complex process of change for average annual temperatures in Xinjiang is not an accidental phenomenon but an inherent reflection of the complex climatic system, a global issue.

Table 1 shows the variance contribution rate of each IMF component and also indicates that inter-annual oscillations are dominant over inter-decadal oscillations in temperature variation. Figure 5 shows the inter-annual and inter-decadal temperature variations in comparison with the original temperature anomaly series, in which the inter-annual temperature is obtained by IMFs IMF1 and IMF2, which represent the inter-annual temperature variation plus trend component, while the inter-decadal temperature is obtained by IMFs IMF3 and IMF4, which are representatives of the inter-decadal temperature variation plus trend component. It can be determined that the reconstructed inter-annual variation trend, which is virtually consistent with the variation trend of original temperature anomaly series, can portray the fluctuations of the original temperature anomaly series in the study period, illustrating the dominant position of inter-annual oscillations in Xinjiang temperature variation. Compared to the original temperature anomaly series trend, the trend component through EEMD can fully reflect the overall trend of the average annual temperature variation in the Xinjiang region from 1957 to 2012. In addition, the reconstructed inter-decadal temperature variation does not adequately portray the temperature anomaly series variation throughout the study period, which may be due to small-scale oscillations excluded from the reconstructed

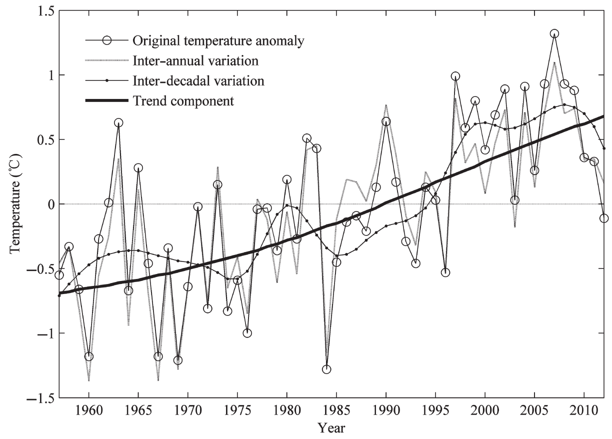

Figure 5. Inter-annual and inter-decadal variations of temperature and their comparisons with the original temperature anomaly.

inter-decadal temperature variation. Although the reconstructed inter-decadal temperature variation does not adequately portray the temperature variations in the late 1980s and early 1990s, it effectively shows that the temperature variation process within the study period can be divided into two distinct variation periods with 1995 as the boundary, before which the temperature rises slowly and after which the temperature rises rapidly, suggesting that the climate mode in Xinjiang before and after 1995 has changed significantly from the original negative-phase-dominated climate mode to the significant positive-phase high-temperature mode.

3.2. The types of temperature variation trend and their spatial distribution

As shown by the analysis in Section 3.1, the temperature in Xinjiang presents an overall increasing trend. In fact, temperature variation trends in different regions are not the same due to the complex topography, circulation type and strength, and other factors. For a more detailed analysis of temperature variation trends in each meteorological station, this article has provided a morphological analysis of temperature variation trend components through EEMD and has found that morphological variations can be broadly divided into four categories: rising type, rising-decrease type, decrease-rising type and decrease type. Table 2 shows the classification results of 16 meteorological stations in Xinjiang used in this article, which includes a total of 10 meteorological stations for rising type, 3 for rising-decrease type, 2 for decrease-rising type and 1 for decrease type.

The temperatures measured by the Xinjiang meteorological stations show an overall rising trend. Locations mainly in the Northwest, the Southwest and the Ili River Valley region of Xinjiang are directly affected by westerly circulation; the Kumul region is also affected as it is located at the intersection of the westerly circulation and Siberian High. Therefore, changes in circulation factors may be an important reason for the overall rising temperatures in these regions. Altay, located at south foot of the Altai Mountains, Karamay, located at northwest margin of

Table 2. Change trend types of temperature for 16 stations in Xinjiang and 6 stations in the areas surrounding Xinjiang.

Station	Period (year)	Trend type	Transition time	Station	Period (year)	Trend type	Transition time
Altay	3, 6, 11, 50	Rising-decrease	1993	Kuqa	3, 6, 11, 26	Decrease	1982
Hoboksar	3, 6, 11, 50	Rising	1980	Kashgar	3, 6, 10, 26	Rising	1993
Karamay	3, 6, 10, 25	Rising-decrease	2005	Bachu	3, 5, 10, 27	Rising-decrease	2005
Jinghe	3, 6, 10, 28	Rising	1992	Tieganlike	3, 7, 10, 34	Decrease-rising	1965
Qitai	3, 7, 11, 42	Rising	1982	Charkhlik	3, 5, 10, 52	Decrease-rising	1975
Yining	3, 5, 10, 25	Rising	1984	Yarkand	3, 5, 10, 21	Rising	1989
Urumqi	3, 7, 11, 29	Rising	1983	Hotan	3, 5, 10, 29	Rising	1991
Turpan	3, 7, 14, 48	Rising	1990	Kumul	3, 5, 10, 29	Rising	1992
Lenghu	3, 5, 10, 20	Rising	1997	Mazongsha	3, 7, 10, 44	Decrease-rising	1988
Hovd	3, 6, 11, 28	Rising	1989	Kara Tjurek	3, 6, 11, 28	Rising	1993
Zharkent	3, 6, 11, 38	Rising	1989	Naryn	3, 6, 14, 39	Rising	1993

The transition time of rise and decrease types refers to the year that temperatures transitioned from negative phase to positive phase and vice versa.

the Junggar Basin, and Bachu, located at the south foot of the Tianshan Mountains, show a rising-decrease trend; Tieganlike and Charkhlik, located at the eastern margin of the Tarim Basin, show a decrease-rising trend; Kuqa, located at the central south of Tianshan Mountain, shows a decrease trend. These three types of changes may be controlled by the terrain. The reasons for the existence of regional differences in temperature variation trends need to be further explored. In addition, EEMD of temperature observations was carried out at six meteorological stations in the areas surrounding Xinjiang (Table 2). The results showed that Mazongshan exhibited a decrease-rising trend due to terrain and other factors, while the remaining five meteorological stations showed a rising trend, which is consistent with the overall rising trend in Xinjiang, indicating that Xinjiang and the surrounding areas are similar in temperature variation trend types.

To further portray the four types of variation trends, this study has selected four typical meteorological stations for further analysis: Jinghe (Figure 6(a)), Altay (Figure 6(b)), Tieganlike (Figure 6(c)) and Kuqa (Figure 6(d)), representing rising type, rising-decrease type, decrease-rising type and decrease type, respectively. Figure 6 shows the original temperature anomaly series in four meteorological stations in comparison with the resulting trend component through EEMD. The results show that the temperature in the four selected stations has a significant nonlinear variation trend, which can depict the entire structure of temperature variation more accurately. In the four meteorological stations, Jinghe temperatures showed a slight rise before 1992, followed by a rapid rise; Altay temperatures showed a significant rise before 1993, followed by a slow decrease; Tieganlike temperatures showed a decrease-rising trend, with a slight decrease trend before 1965 followed by a rapid rising trend; Kuqa temperatures showed a significant decrease trend in the positive phase prior to 1982, followed by a slow decrease trend in the negative phase. In addition, as seen in Table 2 and Figure 6, not only are temperature variation trends different between the single stations and all of Xinjiang, but the transition times of variations are also quite different, indicating that temperature changes are not fully synchronised between the meteorological stations of Xinjiang. The overall climate changes in Xinjiang

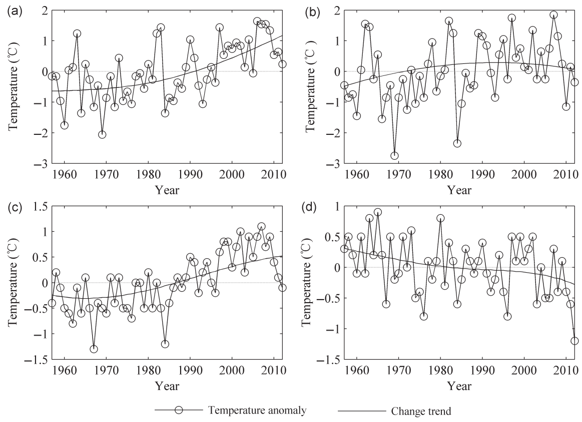

Figure 6. Temperature anomaly and its change trend at four typical meteorological stations.

in 1995 are the result of the superimposed effect generated by temperature variations in each station, which are controlled to a large extent by the inherent change mechanism of the climatic system and the local environment.

4. Conclusions

Based on the temperature anomaly time series from 16 international exchange stations in Xinjiang from 1957 to 2012, the multi-scale characteristics of temperature variability were analysed using the EEMD method. The main findings include the following:

1. In the past 50+ years, the overall temperature in Xinjiang exhibited a significant nonlinear upward trend, and its changes clearly exhibited an inter-annual scale (quasi-3 and quasi-6-year) and inter-decadal scale (quasi-10 and quasi-30-year). In the four quasi-periodic components, quasi-3-year (IMF1) and quasi-6-year (IMF2) periodic fluctuation fall between 90 and 95% confidence interval, indicating that IMF1 and IMF2 are the more significant components that contain more information with actual physical meaning, while the other two components (IMF3 and IMF4) fall within the 80–90% confidence interval, indicating that they contain less information with actual physical meaning.

The variance contribution rate of IMF1 was largest, reaching 47.8%; the contribution of IMF2 was also large, reaching 28.4%; the variance contribution rates of IMF3 and IMF4 were relatively less, with values of 10.11 and 8.58%, respectively, which implied that the inter-annual change had a strong influence on the overall temperature change in Xinjiang.
2 The trend component through EEMD revealed that the temperature variation in Xinjiang during 1957–2012 was an approximately linear (but actually nonlinear) evolution process and that the average annual temperature in Xinjiang had increased significantly since the late 1980s. The reconstructed inter-annual variation trend was virtually consistent with the variation trend of original temperature anomaly series, which can portray the fluctuations of original temperature anomaly series in the study period. Although the reconstructed inter-decadal temperature variation trends only roughly portrayed the process of the temperature variation in Xinjiang, it effectively showed that the temperature variation process in the study period could be divided into two distinct variation periods with 1995 as the boundary, before which the temperature showed a slow rise and after which the temperature rose rapidly, suggesting that the climate mode in Xinjiang before and after 1995 had changed significantly from the original negative-phase-dominated climate mode to significant positive-phase high-temperature mode.
3 The annual average temperature trend had clear regional differences, which can be summarised into four types: rising type, rising-decrease type, decrease-rising type and decrease type. In addition, the transition time of variations were quite different between the single stations and all of Xinjiang, indicating that the temperature variations at each meteorological station in Xinjiang were not fully synchronised and that the temperature variation at each station was controlled to a large extent by the inherent change mechanism of the climatic system and the local environment. The deeper reasons for the significant regional differences in temperature variation trend and transition time need to be further explored.

EEMD is one of the signal analysis methods applicable to nonlinear and non-stationary series, which has significant advantages in data analysis. When EEMD is applied to time series of climatic elements, the reliable and real signals of climate change can be extracted; in particular, the intrinsic time scales of climate change can be available, which facilitates the separation of inter-annual and inter-decadal variation trends from observation sequences in several years and the separation of the general trend of climate change from the time series of climatological observations for several years, which will aid exploring global or regional climate change issues. As climate change is mainly controlled by internal variations of the climatic system at the inter-annual scale, it shows significant natural variability. However, at the inter-decadal scale, climate change is affected by the combined effects of various factors and often mixed with external information, resulting in more complex changes. Therefore, the results of this study confirm that the EEMD method, which is more effective for the decomposition of inter-annual scale of climatic elements, can truly reflect the natural variation characteristics of climatic elements.

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