Early warning signals of abrupt temperature change in different regions of China over the past 50 years*

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In this paper, the early warning signals of abrupt temperature change in different regions of China are investigated. Seven regions are divided on the basis of different climate temperature patterns, obtained through the rotated empirical orthogonal function, and the signal-to-noise temperature ratios for each region are then calculated. Based on the concept of critical slowing down, the temperature data that contain noise in the different regions of China are preprocessed to study the early warning signals of abrupt climate change. First, the Mann–Kendall method is used to identify the instant of abrupt climate change in the temperature data. Second, autocorrelation coefficients that can identify critical slowing down are calculated. The results show that the critical slowing down phenomenon appeared in temperature data about 5–10 years before abrupt climate change occurred, which indicates that the critical slowing down phenomenon is a possible early warning signal for abrupt climate change, and that noise has less influence on the detection results of the early warning signals. Accordingly, this demonstrates that the model is reliable in identifying the early warning signals of abrupt climate change based on detecting the critical slowing down phenomenon, which provides an experimental basis for the actual application of the method.

Keywords: abrupt climate change, critical slowing down, rotated empirical orthogonal function, early warning signal

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1. Introduction

Many studies[1,2] have shown that the evolution of climate systems is not always progressive and may abruptly shift from a relatively stable state to another stable state within a relatively short time. This is called abrupt climate system change, and is likely to occur on a varied temporal scale.[3–5] Abrupt climate change can have a significant influence on the socio-political, environmental, socio-economic development, and general daily life of people.[2,6–8] Thus, it is of great practical significance and scientific value to carry out research into the mechanism, forecast technology, and theory of abrupt climate change on a decadal scale, such as in the 1920s, the late 1970s, and the early 1980s.[9,10] Currently, the research on abrupt climate change mainly focuses on the detection methods and various possible mechanisms,[10–13] but few studies have been conducted on how to judge the occurrence of abrupt climate change by capturing and identifying the early warning signals. However, these early warning signals are key to the prediction of future abrupt climate change.

Abrupt change phenomena are widespread in nature, especially in complex chaotic systems. In the course of orderly evolution, systems are often confronted by shifting among the different states. These shifts are sometimes enormous and even catastrophic. Climate systems always evolve in the vicinity of a critical threshold, and the disturbance of a tiny incident may then induce abrupt climate change. Therefore, some of the characteristics of climate systems near the critical threshold may be considered as early warning signals when judging whether the system is close to the threshold of an abrupt change or not.[2]

An important issue in current climate prediction is whether the early warning signals of abrupt climate change can be identified when the climate system is approaching a critical point. In recent years, scientists have found that critical slowing down phenomena demonstrate significant potential in disclosing whether a complex dynamical system is close to a critical abrupt change.[14–16] Critical slowing down is a concept in statistical physics, and means the approach of a dynamical system to the vicinity of a critical point before a system shifts from one phase state to another. In particular, a dispersed fluctuation phenomenon conducive to the formation of a new phase will appear at the critical point. This dispersed fluctuation is shown in (i) increased amplitude, (ii) extended duration of fluctuation, (iii) a decreased recovery rate from

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disturbance, (iv) reduced recovery capability to the old phase, and other phenomena. The extension of time, the decreased recovery rate, and the reduced recovery capability are called slowing down phenomena.[17] Generally, as the system is approaching a critical value, its current state becomes unstable and changes into another state, and meanwhile, the recovery rate of the system from disturbance becomes slower. Marten Scheffer *et al.*[14] pointed out that when a system is approaching the critical point, critical slowing down phenomena might lead to three possible early warning signals in the dynamics: slower recovery from perturbations, increased autocorrelation coefficient, and increased variance, all of which provide a new way of predicting abrupt climate change. In Ref. [18], the critical slowing down theory was used to study the early warning signals in the Wenchuan earthquake in 2008. The theory has important practical and scientific meaning, not only for a deeper understanding of earthquakes in their active stage, but also for improving the levels of earthquake predictions. Wu, Yan *et al.*[19–21] used the theory to study the early warning signals of abrupt climate change, and discussed the possibility of using the critical slowing down phenomenom. In addition, the applicability of different data methods was investigated, and the conclusion was that different window scales and lag step lengths can affect the stabilities of the calculation results. This resulted in a certain foundation for disclosing early warning signals and further understanding abrupt climate change.

In order to further study the effectiveness of critical slowing down theory for different areas and discuss the temporal and spatial distribution of the early warning signals of climate change, the mainland of China was divided into seven geographical regions based on different rotated empirical orthogonal function (REOF) modes. Critical slowing down theory is then used to study the early warning signals of abrupt climate change in the seven climate subzones. In this paper, the Mann–Kendall (MK) method is adopted to identify the instants of abrupt change in the seven regions, and the temperature data are then analyzed using autocorrelation coefficients that can disclose critical slowing down characteristics. The capture of early warning signals of abrupt climate change is studied by increasing the autocorrelation coefficient. The effectiveness and applicability of the early warning signals for monthly average temperature data with different signal-to-noise ratios are discussed.

2. Data and methods

2.1. Data

The data used are the daily average temperatures of 614 Chinese stations (shown in Fig. 1) between the years 1961 and 2010, supplied by the National Meteorological Information Center of China. In this paper, the monthly average temperature is derived from the daily average temperature. In the calculation, the data between 1981 and 2010 are used for the climate reference state; the anomaly between the original observation data and the climate reference state data is adopted in the computations.

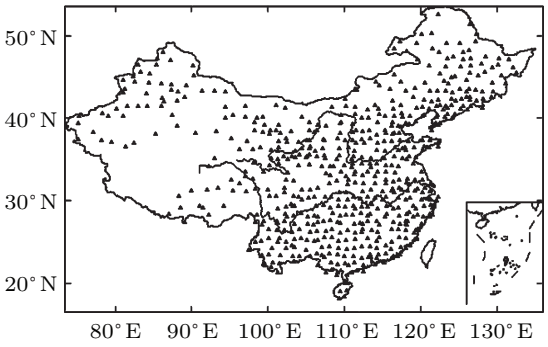


Fig. 1. The distribution of the 614 stations.

2.2. Study methods

1) The variance is the characteristic value that describes the extent of the data deviation in the samples from the mean $\bar{x}$, denoted by s^2, and s is the standard deviation. The computational formulas are, respectively, as follows:

$$s^2 = \frac{1}{n}\sum_{i=1}^{n}(x_i - \bar{x})^2, \tag{1}$$

$$s = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(x_i - \bar{x})^2}, \tag{2}$$

where x_i denotes the i-th datum, and n is the number of data in the sample.

2) The autocorrelation coefficient is a statistic describing the correlation of the same variable at different times. An autocorrelation coefficient with a lag length of j is denoted as $c(j)$. The autocorrelation coefficients with different lag lengths can help to understand the relation between the information at the current time and the information changes at the previous j time, thus judging the possibility of predicting x_{i+j} according to x_i. For the variable x, the autocorrelation coefficient with lag j is

$$c(j) = \frac{1}{n-j}\sum_{i=1}^{n-j}\left(\frac{x_i - \bar{x}}{s}\right)\left(\frac{x_{i+j} - \bar{x}}{s}\right), \tag{3}$$

where s is the standard deviation of the time series with size n, determined by Eq. (2).

3) The relationship between the critical slowing down and the increased autocorrelation coefficient

Critical slowing down will tend towards increases both in the autocorrelation coefficient and the variance of the fluctuation in a stochastically forced system when the system is approaching bifurcation at a control parameter threshold.[14,15] Assume that there is a repeated disturbance of the state variable after each period, Δt (additive noise). Between disturbances, returning to equilibrium is approximately exponential

with a certain recovery speed, λ. This can be described using an auto-regressive model as

$$x_{n+1} = e^{\lambda \Delta t} x_n + s\varepsilon_n, \tag{4}$$

where x_n is the deviation of the system variable from an equilibrium state, ε_n is a random term with a standard normal distribution, i.e., the white noise in the system, and s represents the standard deviation. If λ and Δt are both independent of x_n, this model can also be written as a one-order auto-regressive ($AR(1)$) process:

$$x_{n+1} = cx_n + s\varepsilon_n, \tag{5}$$

where the autocorrelation $c = e^{\lambda \Delta t}$ is 0 for white noise and close to 1 for red noise.

Generally speaking, in the process where a system tends to its critical point, the recovery rate from small-amplitude disturbance will become slower and slower.[22–25] When the system is close to the critical point, the recovery rate λ tends to 0, and the autocorrelation item c approaches 1. Thus, the increased autocorrelation coefficient can be considered as an early warning signal that the system is approaching a critical point.

4) Variance analysis method

The variance analysis method is a common way of calculating a signal-to-noise ratio.[26] The variance analysis of a time domain can be used to estimate how much the inter-annual variance in the temperature and climate index data – caused by weather noise – is. As an example for temperature data, in the case where the daily temperature data are independent of each other, the unbiased estimate of the inter-annual variance in the monthly average temperature (x_{st}) is

$$\sigma_{\mathrm{m}}^2 = \frac{1}{j-1}\sum_{s=1}^{j}(\bar{x}-\bar{\bar{x}})^2,$$
$$\bar{x} = \frac{1}{n}\sum_{t=1}^{n} x_{\mathrm{st}}, \quad \bar{\bar{x}} = \frac{1}{j}\sum_{s=1}^{j}\bar{x}, \tag{6}$$

where n denotes the number of months in a year or the number of days in a season, and j is the total number of years. The climate noise estimate is

$$\sigma_{N_V}^2 = \frac{1}{nj(n-1)}\sum_{s=1}^{j}\sum_{t=1}^{n}(x_{\mathrm{st}}-\bar{x})^2. \tag{7}$$

The signal-to-noise ratio is defined as

$$F_V = \sigma_{\mathrm{m}}^2/\sigma_{N_V}^2. \tag{8}$$

For the temperature series, each year data contains 12 months' data, so n is 12; the observations are from 1961 to 2010, so j is 50.

5) The Mann–Kendall method

The MK method[10,27] is a non-parametric statistical test method that is easily computed and can be used to determine the starting time of the abrupt change, so it is often used for abrupt change detection.

For a time series $x_1, x_2, \ldots, x_N$, the statistical quantity is defined as

$$s_k = \sum_{i=1}^{k} m_i \quad (k = 2,3,\ldots,N), \tag{9}$$

where m_i denotes the cumulative number to a sample x_i greater than x_j $(j = 1,2,\ldots,i)$. First, suppose that the original series $x_1, x_2, \ldots, x_N$ is randomly independent, and the mean value and variance of s_k can be expressed, respectively, as follows:

$$\begin{cases} E[s_k] = k(k-1)/4, \\ \mathrm{var}[s_k] = k(k-1)(2k+5)/72, \end{cases} \quad (2 \le k \le N). \tag{10}$$

The standardized treatment of s_k is

$$u(s_k) = (s_k - E[s_k])/\sqrt{\mathrm{var}[s_k]}, \tag{11}$$

where $u(s_k)$ is the standard normal distribution, and the probability of $\alpha_1 = \mathrm{prob}(|u| > |u(s_k)|)$ can be obtained by computation or by visiting a statistical table. A significance level α_0 is given, and if $\alpha_1 < \alpha_0$, this means that the series will have an obvious trend toward the increase or decrease. The whole $u(s_k)$ $(1 \le k \le N)$ will form a curve, C_1, and its changing trend can be known through a reliability test.

After that, the inversion of the series undergoes the same operation as mentioned above. $\bar{m}_i$ denotes the cumulative number to the i-th sample x_i greater than x_j $(j = 1,2,\ldots,i)$; when $i' = N+1-i$, if $\bar{m}_i = m_i$, then $\bar{u}(s_i)$ in the reverse series is given in the following formula:

$$\begin{cases} \bar{u}(s_i) = -u(s_i), \\ i' = N+1-i, \end{cases} \quad (i, i' = 1,2,\ldots,N), \tag{12}$$

$\bar{u}(s_i)$ is expressed as C_2. If the intersection of the curves C_1 and C_2 is located between the reliability lines, then this intersection is the starting time instant of an abrupt change.

3. Results and discussion

3.1. REOF subzones

Figure 2 shows the distribution of the first seven REOF modes and their monthly average temperature subzones over the past 50 years in China. The subzones are those areas that should have geographical contiguity with the absolute loading value greater than or equal to 0.5 in the same loading vector field. Table 1 shows the variance contribution rate and the cumulative variance contribution rate of each REOF mode. The cumulative variance contribution rates of seven modes reach 72.48% in total, and are consistent with the requirements of REOF partition. It is easy to find that the first three models are main contribution modes, their cumulative variance contributions reach 54.74%, and that the contribution rates of the other four modes are below 10%, which may relate to the geographical distribution of more stations in eastern China and fewer in western China.

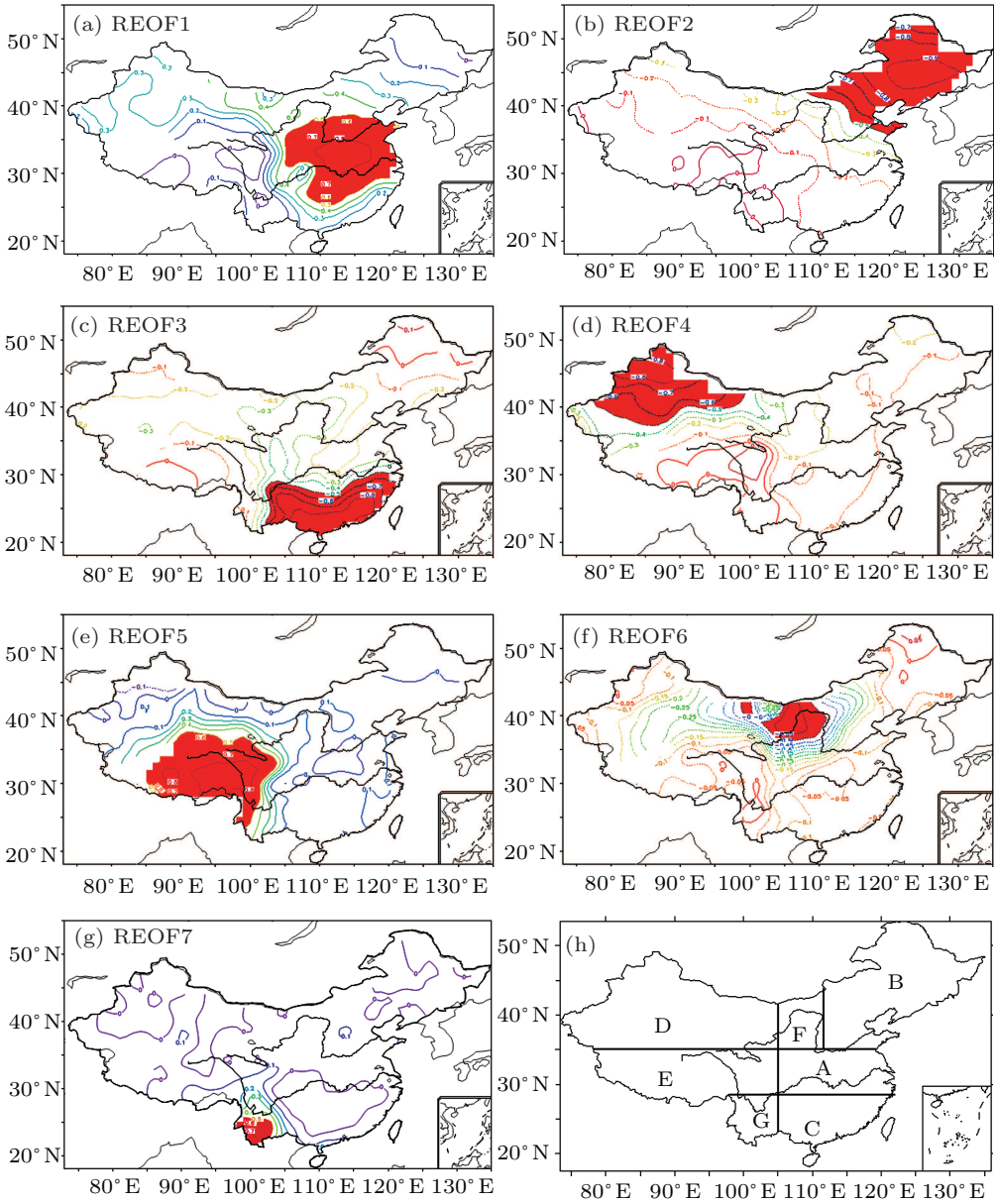


Fig. 2. (color online) The first seven rotated loading vector fields and temperature subzones over 50 recent years in China. (a) REOF1: the middle and eastern part of China; (b) REOF2: the northeastern part of China; (c) REOF3: the southern part of China; (d) REOF4: the northwestern part of China; (e) REOF5: Tibet; (f) REOF6: the Hetao area of the Yellow River; (g) REOF7: Yunnan; and (h) the seven subzones.

Table 1. The variance contribution rates and cumulative variance contribution rates of all the REOF modes.

REOF modal	1	2	3	4	5	6	7
Variance contributions/%	19.20	17.83	17.71	6.01	5.76	3.69	2.28
Cumulative variance contributions/%	19.20	37.03	54.74	60.75	66.51	70.20	72.48

By considering the possible regional overlaps in all the modal distributions and including all the information in 614 stations, China is roughly divided into seven regions according to the distributions of seven REOF modes, as shown in Fig. 2(h). The regional average computation method to calculate the monthly average temperature in each region is used. The weighted average method is adopted according to the grid area by Jones *et al.*[28] as follows:

$$S_k = \sum_{i=1}^{n} \cos(w_i) S_{ik} \Big/ \sum_{i=1}^{n} \cos(w_i), \qquad (13)$$

where S_{ik}, represents the observation in the k-th month at the i-th station, w_i the latitude at the i-th station, S_k the regional average in the k-th month in a region, and n the number of stations in a region.

The seven regions are (a) the middle eastern part of China, which mainly includes the middle and lower reaches of the Yangtze River and covers 128 stations from 105° E to 135° E and from 27.5° N to 35° N; (b) the northeastern part of China, including northeast China, most of the Shanxi Province, Beijing, Tianjin, and other areas, covering 175 stations from 111° E to 135° E and from 35° N to 55° N; (c) the southern

part of China, including Guangdong, Guangxi, Fujian, Hunan, Jiangxi, and others, covering 104 stations from 105° E to 135° E and from 15° N to 27.5° N; (d) the northwestern part of China, including Xinjiang, Gansu, Ningxia, Qinghai, the west of Inner Mongolia, and others, covering 91 stations from 70° E to 105° E and from 35° N to 55° N; (e) the Tibetan region, including Tibet, Sichuan, and others, covering 49 stations, from 70° E to 105° E and from 27.5° N to 35° N; (f) the Hetao area of the Yellow River, including middle Inner Mongolia, Shanxi, and others, covering 33 stations, from 105° E to 111° E and from 35° N to 55° N; and (G) Yunnan, which includes the Yunnan province, the south of the Sichuan province, and other places, and covers 34 stations, from 70° E to 105° E and from 15° N to 27.5° N. Considering the fact that the climate changes in all the subzones divided according to the REOF are consistent and their central distributions all have high loads, the regional average temperature could be used to calculate the instants of abrupt change in this region and to find early warning signals.

3.2. Abrupt change detection in each region

Figure 3 shows the abrupt change detection results of the monthly average temperature in each subzone in China based on the REOF. According to the MK method, if the intersection of curves C_1 and C_2 is located between the reliability lines ($\alpha_0 = 0.01$), then this intersection is the starting time of the abrupt change, and thus we can obtain the time of the abrupt temperature changes in each region (as shown in Fig. 3(h)). It is necessary to note that if curve C_1 goes beyond the reliability line, and the intersection of curves C_1 and C_2 is outside the reliability interval, then this intersection should not be rashly determined as an abrupt change point. In the case of detecting abrupt change, the combined use of a couple of methods can reduce some of the mistakes.[1] The intersections of C_1 and C_2 in Figs. 3(d)–3(g) are on the reliability lines, and the others are located between the reliability lines. Therefore, the abrupt change position in each subzone can be identified by the MK method. Wu *et al.*[21] utilized the first-level meteorological geographical divisions of China to detect the instants of abrupt climate change in each region, and their results are very similar to what we found in this paper. The area from the Yellow River to the Yangtze River valleys in Wu *et al.*'s paper corresponds to the middle-eastern part of China in this paper, and the detected instants of abrupt change are all around 1995. The northeast and northern parts of China, and Inner Mongolia in Wu *et al.*'s paper correspond to the northeastern part of China in this paper, and the detected instants of abrupt change are around 1990. For the other areas, the detected instants of abrupt change are the same. However, the abrupt change in the southern part of China in Wu *et al.*'s paper occurred in 1992, while the detected abrupt change in this paper is 1995. This is because the area divisions are somewhat different. The Hetao area of the Yellow River is particularly studied and analyzed here because the climatic characteristics in this area are not the same as those in Inner Mongolia, northern China and northwest China. It can also be indicated from the comparative analysis that the subzones derived from the use of REOF are perfectly relevant to China's first-level meteorological geographical division. Both of them grasp the climatic characteristics in each region, and thus the results prove the quality of the REOF subzones in this paper.

3.3. Early warning signals of autocorrelation coefficients

The signal detection results of the autocorrelation coefficients in the monthly average temperatures are given in Fig. 4. It is worth mentioning that the lag time and the moving steps in Fig. 4 have different meanings. The lag time means that the original series in the selected window size is delayed by the selected step length and another series of the same size is obtained. The obtained and previous series are used to compute the correlation, namely its own lag correlation. The moving steps means that the series in the selected window size slid into a fixed step length to obtain a new series, and the autocorrelation coefficient of the new series is determined. According to our study, a reasonable selection window and lag time can improve the quality of the detection result.[19,20] The aforementioned theoretical analysis shows that the critical slowing down leads to a reduction in the internal rate of change in the system, and at any moment causes the state of the system to increasingly resemble its previous state, so the autocorrelation coefficient approaches 1. The increase in the autocorrelation coefficient when the climate systems approach the critical point, which is one kind of critical slowing down phenomenon, indicates that the climate system may soon change abruptly. The phenomenon of increased autocorrelation coefficients emerges at the arrowed positions in Figs. 4(a)–4(g), and it can be deemed that the early warning signals of abrupt climate change occur at this time. Figure 4(h) clearly shows the critical slowing down phenomenon of an increase in the autocorrelation coefficient, which means the early warning signals of an abrupt climate change. The signals that emerged 5–10 years before the occurrence of abrupt climate change are according to the detection results of the autocorrelation coefficients in all the regions, regardless of the differences in the instants of abrupt temperature change. This is a significant indicator for the occurrence of an abrupt climate change, which verifies the effectiveness of early warning signals of abrupt climate change based on autocorrelation coefficients. It can be concluded from Fig. 4 that the early warning signals of abrupt climate change in middle eastern China, northeastern China, southern China, and

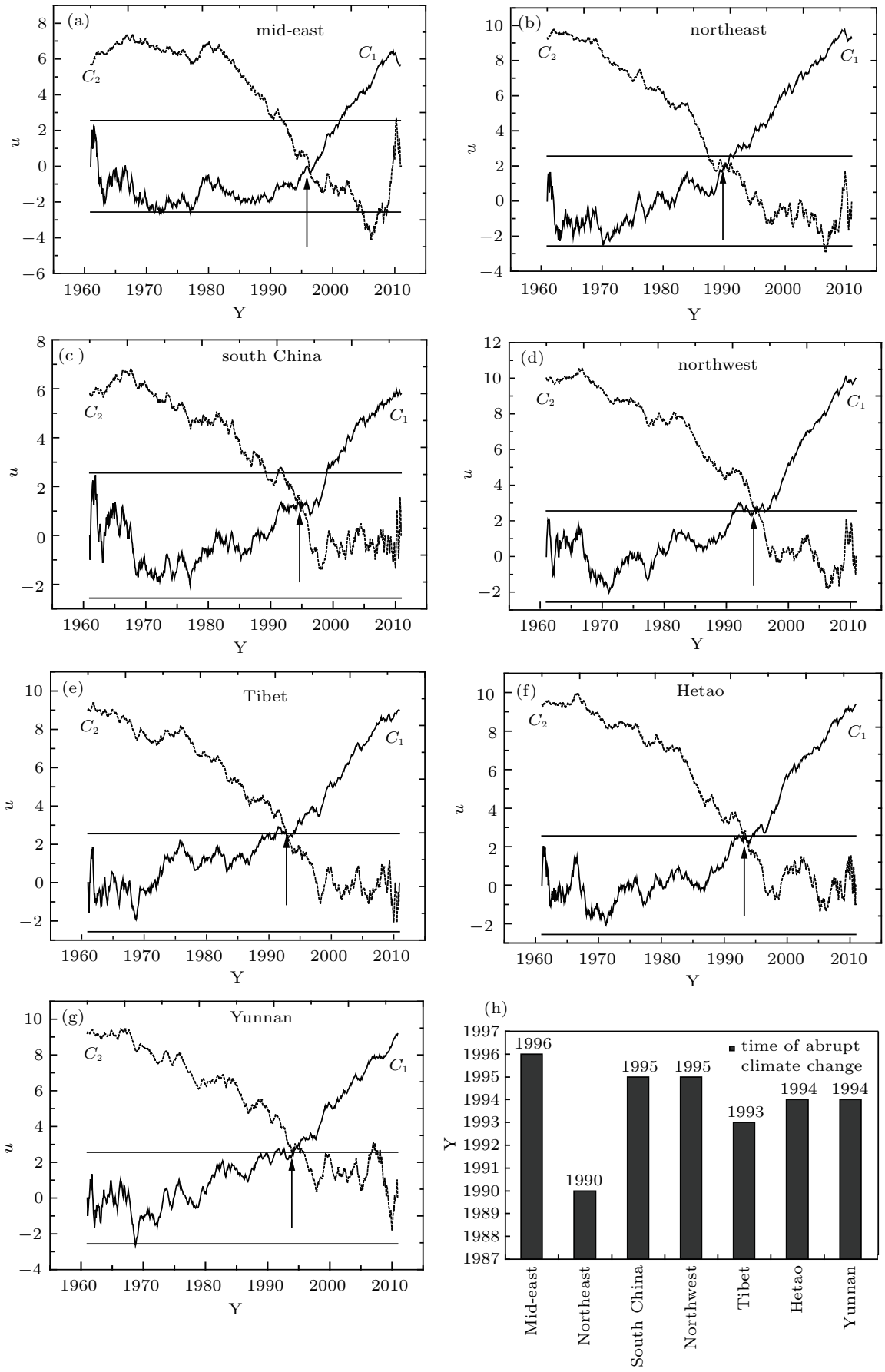


Fig. 3. Abrupt change detection of the monthly average temperature in all the regions in China. MK detection in (a) middle-eastern China; (b) northeastern China; (c) southern China; (d) northwestern China; (e) Tibet; (f) the Hetao area of the Yellow River; (g) Yunnan; and (h) the comparative analysis of the time of abrupt change in all the regions.

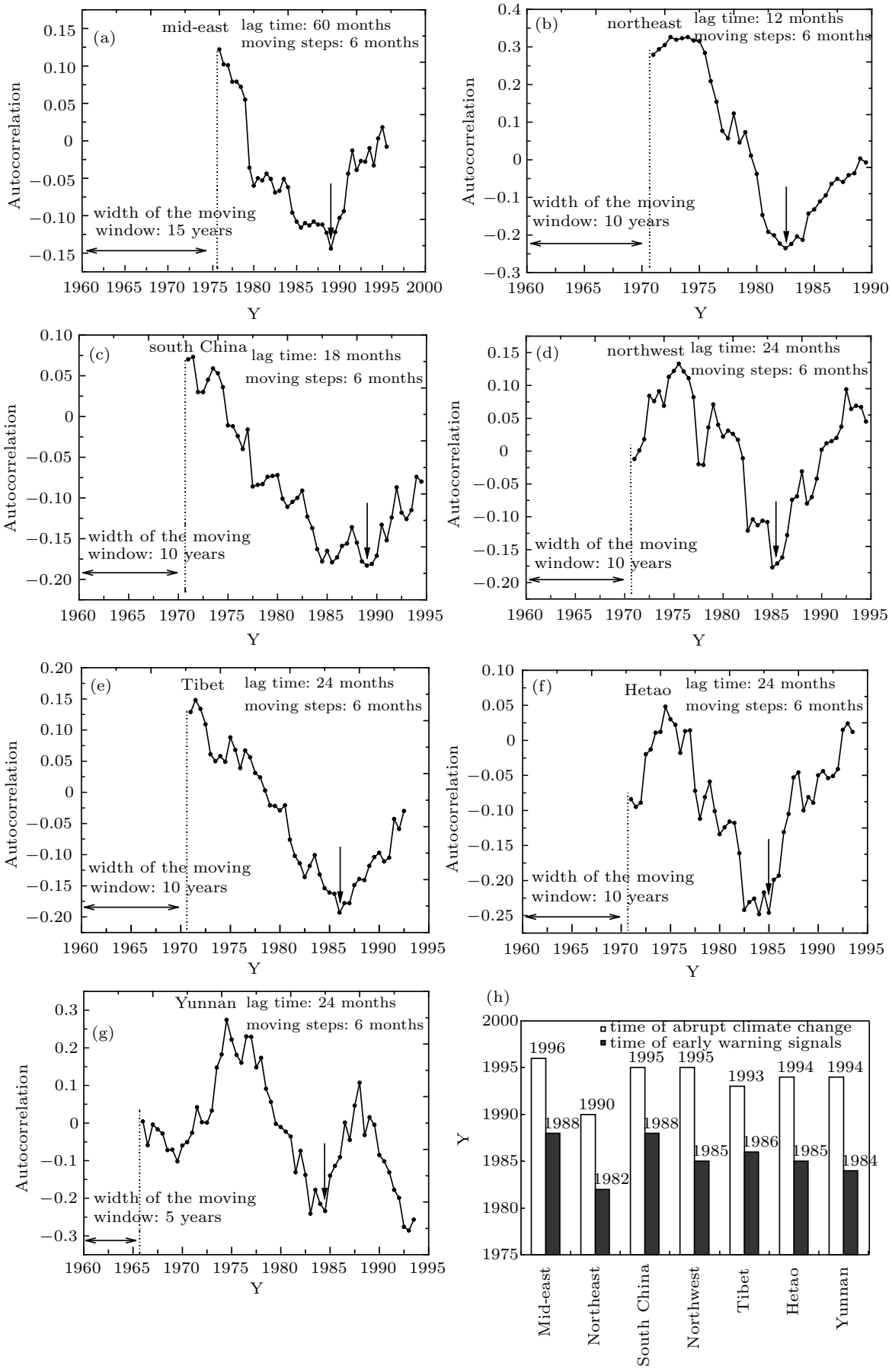


Fig. 4. Autocorrelation signal detection and comparisons of the monthly mean temperature in each region of China. (a) Middle-eastern China; (b) northeastern China; (c) southern China; (d) northwestern China; (e) Tibet; (f) the Hetao area of the Yellow River; (g) Yunnan; and (h) comparison of the results in all the regions.

other regions are superior to those in northwestern China, the Tibetan region, and Yunnan. This might be closely related to the fact that we take into consideration more stations in eastern China but fewer in western China, and that there is a difference in the climatic characteristics between both areas.

3.4. The effect of noise on the early warning signals of abrupt climate change

Table 2 shows the signal-to-noise ratios, the time of abrupt change, and the starting instants of the early warning signals of the monthly average temperature in each region. The variance analysis method is first used to obtain the climate noise and the signal-to-noise ratios of the monthly average temperature in each region of China. Comparative studies are conducted on the applicability and universality of the autocorrelation coefficient signals serving as early warning signals of abrupt climate change according to different signal-to-noise ratios. According to Table 2, the climate noise is different in each region, being relatively large in the northeastern part of China, the Hetao area of the Yellow River, and the northwestern part of China. The signal-to-noise ratios are relatively high in the Tibetan region and Yunnan, while the southern part of China has minimal signal-to-noise ratio. All the signal-to-noise ratios are in a range from 1 to 5, falling within a relatively normal range. In the analysis mentioned above, it can be found from the detection of the monthly average temperature in each region that the autocorrelation coefficients can be used as early warning signals of abrupt climate change, and their applicability is quite good. According to the data with different signal-to-noise ratios, the increased autocorrelation coefficient signals can be applied to all critical slowing down phenomena. It is found that the noise has little effect on the detection results of the signals, which verifies the universality of the method.

Table 2. The values of the signal-to-noise ratio (SNR), the abrupt change time, and the early warning signal instants of the monthly average temperature in each region of China.

Region	Time of abrupt change/year	Autocorrelation signal/year (lead time/year)	Inter-annual variance σ_m^2	Climate noise variance $\sigma_{N_V}^2$	Signal-to-noise ratio (SNR) $F_V = \sigma_m^2/\sigma_{N_V}^2$
Mid-eastern part	1996	1988(8)	0.25	0.09	2.90
Northeastern part	1990	1982(8)	0.48	0.12	3.97
South	1995	1988(7)	0.16	0.09	1.83
Northwestern part	1995	1985(10)	0.41	0.11	3.78
Tibet	1993	1986(7)	0.21	0.05	4.25
Hetao	1994	1986(8)	0.51	0.14	3.77
Yunnan	1994	1984(10)	0.19	0.04	4.76

4. Conclusions

The critical slowing down phenomenon that is observed before an abrupt change occurrence in a complex dynamical system could be used as an early warning signal to indicate the occurrence of the abrupt change. Using autocorrelation coefficients that indicate critical slowing down phenomena to study the temperature precursor signals in all the studied regions of China can not only deepen our understanding of the precursor signals, but also provide new ways of judging the reliability of climate abnormalities.

In this paper, we analyzed the physical basis and statistical significance of critical slowing down phenomena. The mainland of China was divided into seven areas using the REOF method. These regions are the middle-eastern, northeastern, southern and northwestern parts of China, Tibet, the Hetao area of the Yellow River, and Yunnan. Using the MK detection method, the instant of abrupt climate change in each subzone was detected. Through the monthly average temperature data derived from each region of China, we conducted an investigation into the early warning signals of abrupt change. First, the autocorrelation coefficients were examined after removing the inter-decadal change trends from the monthly average temperature observation data in all the regions. Then, retrospective testing was conducted on the critical slowing down phenomena. The results showed that the autocorrelation coefficient that appears in the monthly average temperature data increases to different extents in the different regions. This phenomenon appears before abrupt climate change occurs, which indicates that critical slowing down phenomena could be used as early warning signals of abrupt climate change. For different signal-to-noise ratios, autocorrelation coefficient signal detection could be applied, proving that noise has little effect on the early warning signals of abrupt climate change, and also verifying the universality of the method. Although the observational data in the different subzones all have a slowing down phenomenon, the occurrence times of the phenomena are not exactly the same. Overall, the detection results in the middle-eastern, northeastern, and southern parts of China were found to be superior to those in the northwest of China and the Tibetan region. This may be closely related to there being

more stations in the eastern than western part of China, and also to their climatic characteristics. Although this is a preliminary study of the early warning signals of abrupt climate change, the results show that the critical slowing down phenomenon provides the possibility of a detailed understanding of the precursor signals of the observation data, and can judge whether any abnormality tends to the critical stage, thus improving abrupt climate change predictions. The application of critical slowing down theory to the study of the early warning signals of abrupt climate change is of practical and scientific significance in understanding abrupt climate change and discovering the early warning signals.

It is worth noting that according to the monthly average temperature data in all the studied regions of China, the dynamic autocorrelation coefficient increase resulting from the critical slowing down phenomenon may be an early warning signal prior to the occurrence of abrupt climate change. These results are only from our preliminary study. In further work, areas such as the spatial extension where critical slowing down phenomena emerge before the occurrence of abrupt climate change, the relationship between the critical slowing down phenomena and the intensity of abrupt climate change, the different effective factors in different regions, and the critical slowing down characteristics in different cases of external forcing should be studied.

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