Chinese Science Bulletin 2004 Vol. 49 No. 4 410—415

The forecast of seasonal precipitation trend at the north Helan Mountain and Baiyinaobao regions, Inner Mongolia for the next 20 years

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Abstract **By using Caterpillar-SSA analysis method, through the process of embedding, singular value decomposition, grouping and diagonal averaging, the seasonal precipitation trend at north Helan Mountain and Baiyinaobo regions, Inner Mongolia for the next 20 years is forecasted. The results show an increasing precipitation trend from 1992 to 2004. In the subsequent decade the precipitation should reduce quickly, and it will reach a minimum near 2012 to 2014 in both regions. The drought caused by the decrease of the precipitation from May to July in the north Helan Mountain area during the period of 2013—2014 is probably quite similar to that around 1929. Further, the period of precipitation gradual increase follows in the researched regions.**

Keywords: north Helan Mountain, Baiyinaobao, precipitation trend, forecast.

DOI: 10.1360/03wd0410

One of the purposes of studying the climatic variation in the past is to predict the climate in the future. Tree rings have attracted great attention of geo-environmental and climatic scientists due to its quantity, high resolution (season to year), continuity, and reliability as well. The CLIVAR project (Climate Variability and Predictability Program), presented by WCRP (World Climate Research Program) in 1995, especially emphasizes the study of the interannual high-resolution climate variation records during the past 100 to 1000 years and its predictability in the future. Tree ring has been listed as one of the key methods in both programs.

However, there has been no report on prediction of the trends of future climate variation using tree-ring data in China so far. Based on tree-ring data, dendrochronologists have made some predictions, for example, in the late 1960s Stockton successfully predicted an increasing precipitation trend of the following 20 years of Morocco (Stockton, personal communication). But the case is very few except for this one. Dendroclimatology research has made great progress in recent years in China. Some climatic indices, such as temperature, precipitation, and humidity index of the past several hundred years in some regions have been reconstructed and many valuable data were obtained[1—7]. Undoubtedly, the tree-ring series will play an important role in future climate prediction because they follow the principles requested by statistical prediction, such as long-term data, continuity, analogy, correlation, dynamics, and periodicity. At present, what the Chinese people especially concerned is how the climate will change in northern China in the future. Based on tree-ring reconstructions and the Caterpillar-SSA method, we are going to find a time series structure, such as the trend and components of the series, and extrapolate the time series in this paper. A tentative prediction of the natural variation trend of the seasonal precipitation in the north Helan Mountain and Baiyinaobao, Inner Mongolia, for the future 20 years will be made.

1 Material and method

The tree-ring data used in this paper are derived from the following two regions (Fig. 1):

(1) The Helan Mountain in western Inner Mongolia. Tree-ring data are taken from ref. [8], representing the precipitation from May to July with the time span of 271 years (1726—1997). In this paper we regard the reconstruction, after 11-a moving average, as the initial series (the length is 261 years, 1731—1992). There are two reasons. First, our purpose is to predict the next 20-a trend, and that the new series after 11-a moving average can better reflect its variation trend (there is a strong 11-a cycle in the original series). Second, the original paper shows that the explained variance of the reconstruction series reaches up to 82% after 11-a moving average (r = 0.91, F = 156.9, p < 0.05).

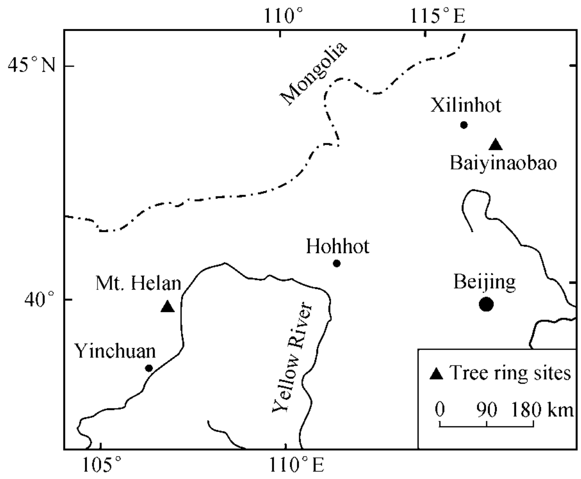

Fig. 1. The location of studying sites.

(2) The Baiyinaobao region in eastern Inner Mongolia. Tree-ring data are taken from ref. [3], representing the precipitation from May to early July (to July 10th) with 160 years (1838—1999). There exists an 11-a cycle in the original series. In terms of the two reasons above, 11-a moving average was made to the original series and then produced the initial series with the length of 150 years (1843—1994).

Fig. 7 in ref. [8] shows that these two precipitation series, 1000 km apart from each other and both in the margin of the East Asia Summer Monsoon, display strong synchronous variation trend during their common period of the past 150 years. This makes it possible to compare the prediction results between the two regions.

There are many forecasting methods in classical statistics, such as regression, time series smoothing, autoregression filtering, Box-Jenkins and so on[9]. We use the Caterpillar-SSA1) method, which has been developed in recent years, to make forecast in this paper. Caterpillar is a novel and powerful time series analysis and forecasting method. Its purpose is to distinguish the spatial and temporal agglomeration-model from the given regular sampling plots. Basically it is a transformed EOF analysis. The strongpoint of Caterpillar-SSA is that it is a model-free method. The extractions of long-term trend, seasonal fluctuation, periodicity, and noise components are worked out by using eigenvector analysis. Then the variation trend could be forecasted[10−13].

There are four steps for Caterpillar-SSA analysis:

(1) The embedding step. A one-dimensional time series $F = (f_1, f_2, \cdots, f_N)$ is transferred to a L-dimensional time series $X_i = (f_i, f_{i+1}, \cdots, f_{i+L-1})^T$, $(i = 1, 2, \cdots, K = N - L + 1)$. This delay procedure gives the first name (Caterpillar) to the whole technique. Vectors X_i form the columns of the trajectory matrix: $\boldsymbol{X} = [X_1, X_2, \cdots, X_K]$. The sole and very important parameter of the embedding step is the maximum time lag L, also named window length. L should be big enough but not greater than a half of the series length. Generally the bigger L is, the more sensitive the distinguishing power of spectrum is, and it is easy to recognize the close peaks. Under the proper choice of window length L singular vectors in a sense repeat the behavior of the corresponding time series components. In general, the times series with signals of q cycles have additional noise too. Caterpillar could extract q cycles, but rest eigenvalue will not be zero[14].

(2) The singular value decomposition step. It is to decompose the trajectory matrix into a sum of rank-one bi-orthogonal elementary matrices $\boldsymbol{X}_i$ ($i = 1, 2, \cdots, L$) and this gives the second name (singular value decomposition) to the technique. Then we have $\boldsymbol{X} = \boldsymbol{X}_1 + \boldsymbol{X}_2 + \cdots + \boldsymbol{X}_L$. Elementary matrix $\boldsymbol{X}_i$ is determined by the equality $\boldsymbol{X}_i = s_i U_i V_i^T$, where s_i (i th singular value) is the square root of the i th eigenvalue of the matrix $\boldsymbol{X}\boldsymbol{X}^T$; U_i and V_i stand for left and right singular vectors of the trajectory matrix respectively[15]. We assume that eigenvalues s_i^2 are arranged in the decreasing order of their magnitude. The collection (s_i, U_i, V_i) is called the i th eigentriple of the matrix $\boldsymbol{X}$[16,17].

(3) The grouping step. It is to split the L elementary matrices into several groups (m) using cluster analysis method and to sum the matrices within each group to form the compound matrix $\boldsymbol{Y}_i$ ($i = 1, 2, \cdots, m$). Also, $\boldsymbol{Y}_i = \sum_{l \le j \le L} \boldsymbol{X}_j$ (the value of j is determined by cluster analysis results). The result of this step is another decomposed formula of the trajectory matrix as a sum of several resultant matrices: $\boldsymbol{X} = \boldsymbol{Y}_1 + \boldsymbol{Y}_2 + \cdots + \boldsymbol{Y}_m$.

(4) Diagonal averaging. The last step transfers each resultant matrix into a time series, which is an additive component of the initial series F. Given that y_{ij} stands for an element of a matrix $\boldsymbol{Y}$, then the kth term of the resulting series is obtained by averaging of y_{ij} over all i, j such that $i + j = k + 1$. Diagonal averaging is a linear operation and maps the trajectory matrix of the initial series into the initial series itself[16,17]. In this way we obtain several additive components by decomposing the initial series. The result is the expansion: $F = F_1 + F_2 + \cdots + F_m$.

The first two steps together are considered as the decomposition stage of 'Caterpillar'-SSA. And the last two steps form the reconstruction stage. Based on the principles above, we analyzed the precipitation series of the north Helan Mountain and Baiyinaobao regions.

2 Decomposition of precipitation series

According to the data length, we chose 130 and 75 years as the window lengths (L) for the precipitation series for the north Helan Mountain and the Baiyinaobao region respectively. Many tests show that small changes of L, near the window length, do not influence the singular value decomposition of the initial series. Caterpillar-SSA can identify the fluctuations with the cycles at $L/15$—L. The result of singular value decomposition indicates that the maximum spectral densities lie in 11, 20—24 and 40—53 years. The dominant periods are 40 and 11 years (Fig. 2(a), (b)), which explained 40.8% and 49.7% of the precipitation variances respectively. Meanwhile, there are some other components.

1) Golyandina, N., Nekrutkin, V., Solntsev, V., "Caterpillar"-SSA technique for analysis of time series in economics, Saint-Petersburg State University.

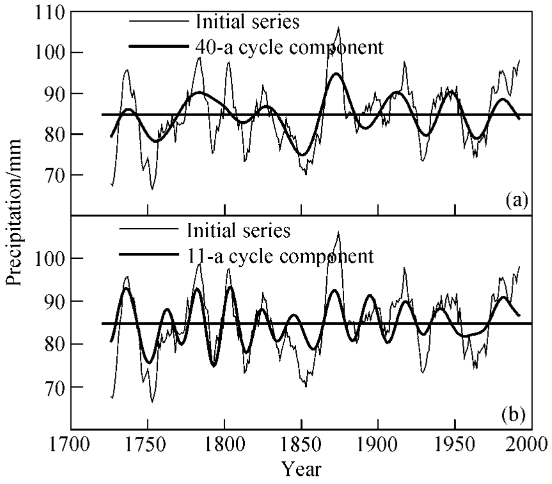

Fig. 2. The components of 40- and 11-a cycles extracted from the precipitation series of the north Helan Mountain. The horizontal line is the mean value of the precipitation.

Caterpillar-SSA analysis shows that the 22-a cycle is dominant in Baiyinaobao rainfall series, and it has a strong effect on precipitation trend variation, especially before 1945. This is the same result as that obtained from wavelet analysis in ref. [3]. The 22-a cycle explained 45.6% of the total precipitation variance.

The singular component grouping was done by cluster analysis with the use of the correlation matrix obtained from 130 singular reconstructions. We used the Ward method and the Euclidean distance for cluster analysis[18]. The process is spread by the tree diagram. Take the north Helan Mountain for example: we divided the singular vector of the initial precipitation series into five groups using this method. The first one (S1) is the combination of 20, 43, and 53-a periods, which explains 79.3% variance of the initial series. The second one (S2) is the combination of 19, 30, and 68-a cycles, explains 12% variance. The low-frequency components presented by S1 and S2 explain 91.3% variance of the initial series. It should be noted that the low-frequency components behave quite stably on all time periods of reconstruction with no significant increase in an average level of precipitation (Fig. 3).

The third one of the singular decomposition (T1) is the high-frequency components with cycles of 12—13 years, explaining 5.8% of the total variance of the initial series. The fourth one (N1) is a very unstable component with a 7.5-a cycle, a random trend in terms of the obtained reconstruction figure, which explains 1.8% of the initial series variance. The fifth one (N2) is white noise, a component with normal distribution, which is the high-frequency fluctuation with the period of 2-a and explains 1.1% of the initial series variance.

Thus, the initial series has been transformed into additive sequence of three basic components: the signal (S1 + S2), the trend (T1 + N1), and the noise (N2). Since N2's explained variance is too small, only 1.1%, it is possible to make the assumption that it is enough to use the first four grouping components, which explain 98.9% variance of the initial series, for the high-quality short-term forecast. Fig. 4 is the result of overlapping the first four components. The noise-free components in Fig. 4(a) will be the basis of trend extrapolating, or forecasting.

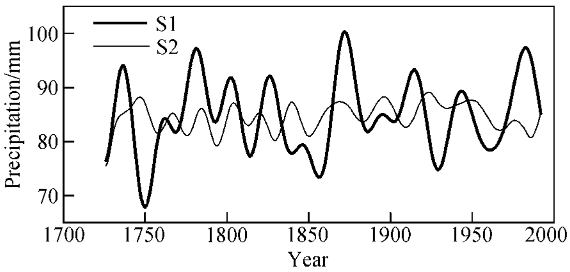

Fig. 3. The decomposed low-frequency components of S1 and S2 from the precipitation series in the north Helan Mountain.

Verification of the obtained forecasting model by two independent methods, vector and recurrent[13], has shown very good concordance in dynamics of both the initial and the modeled reconstruction from 1873 to 1980.

1726—1872 is the reconstruction period, and 1873—1980 is the calibration period. In the vector method the correlation is 0.89 (N = 111, R^2 = 79.2%, p < 0.000001) and the mean-square error is 12.4. In the recurrent method, correlation is 0.93 (N = 111, R^2 = 86.5%, p < 0.000001) and the mean-square error is 10.0. The results from these two verification methods are practically coincident. According to the forecasting theory[19], the larger the R^2 is, the smaller the mean-square error is, the better the forecasting result will be. Obviously, the recurrent method is more accurate because its R^2 is larger and the mean-square error is smaller than those of the vector method (Fig. 5).

It allows us to make the assumption that the forecasting model obtained from signal (S1 + S2) and trend (T1 + N1) is adequate.

The same procedures as stated above are applied in the analysis for the precipitation series at Baiyinaobao, needless to give unnecessary details any more. Fig. 6(a) shows the result of overlapping all first four components, signal (S1 + S2) and trend (T1 + N1), which explain 98.4% variance of the initial series. The noise component in Fig. 6(b) explains only 1.6% variance of the initial series.

3 Forecasting results

Based on the method above, we extrapolate seasonal precipitation series for 30 years starting from 1992 to 2022 in the north Helan Mountain, and 1994 to 2024 in Baiyinaobao (Fig. 7). The peak value of the precipitation from May to July occurs in 2002—2004 in the north

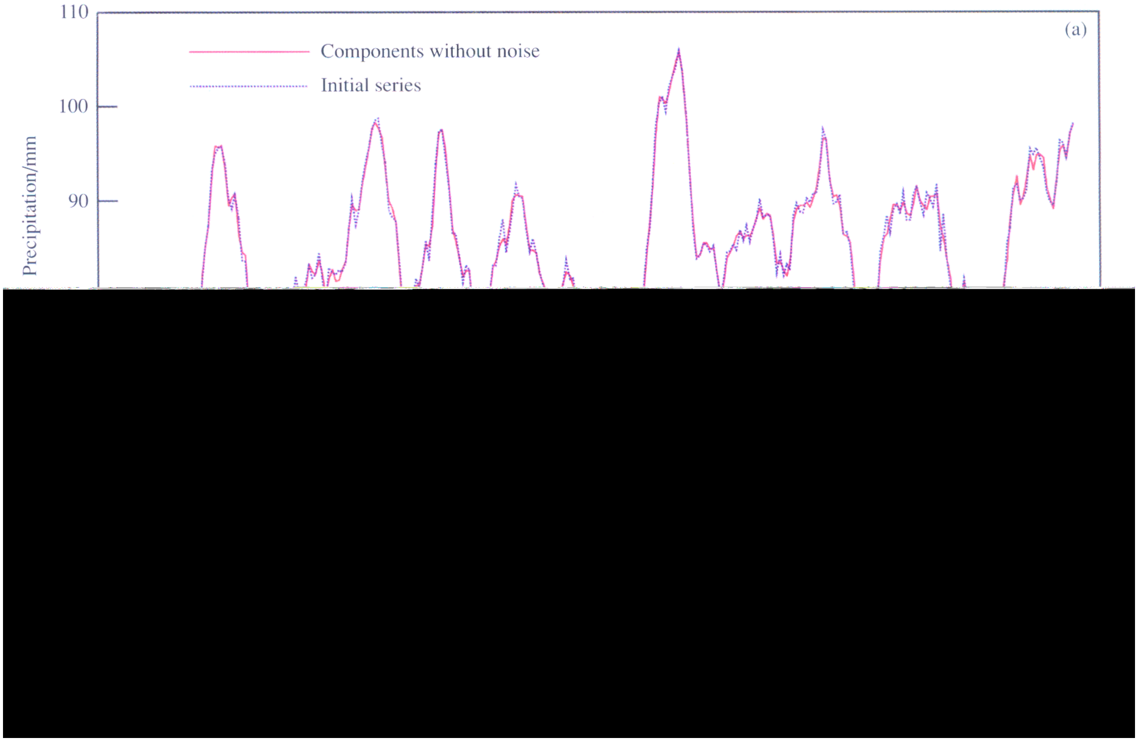

Fig. 4. (a) The result of overlapping signal (S1 + S2) and trend (T1 + N1) in the precipitation series of the north Helan Mountain. It explains 98.9% variance of the initial series. (b) Noise component, accounting for 1.1% variance of the initial series.

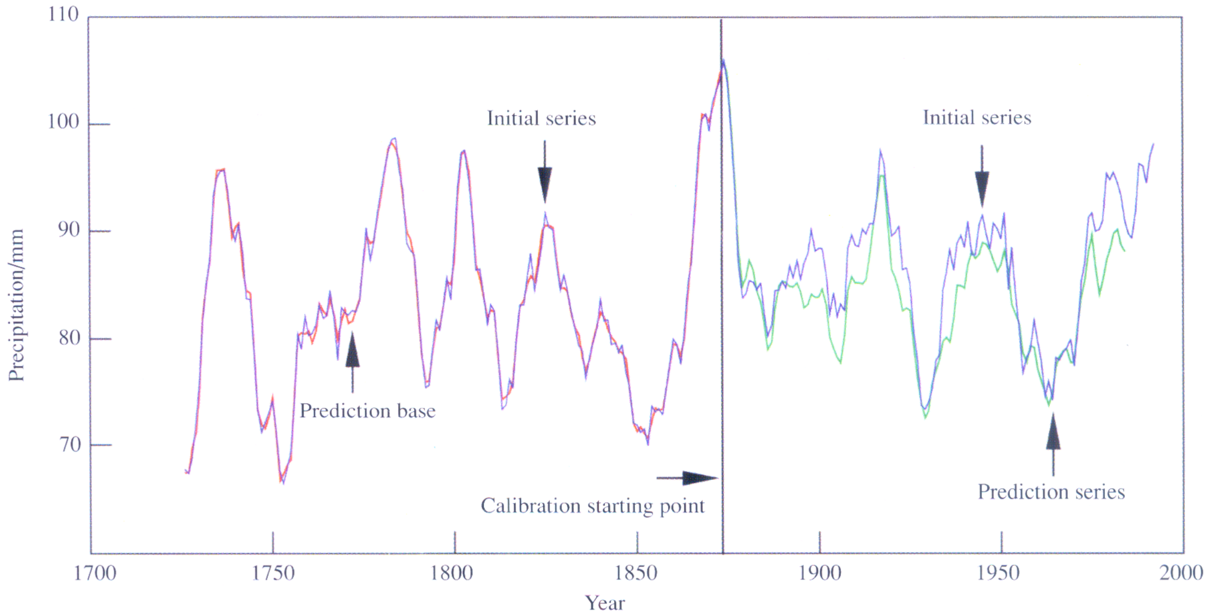

Fig. 5. The comparison between the initial, the modeled and the recurrent verification series (the verification period 1873—1980).

Helan Mountain. Afterwards, the precipitation will gradually decrease in the following 10 years and reach the lowest value in 2013—2014, the drought degree at that time is probably quite similar to that around 1929. Consequently the precipitation will increase, but still lower than the average (1731—1992) and far below the mean of 1970—2002.

In Baiyinaobao, the peak value of the seasonal precipitation from April to early July occurs in 2004, and then decrease follows. The precipitation decreasing slips into

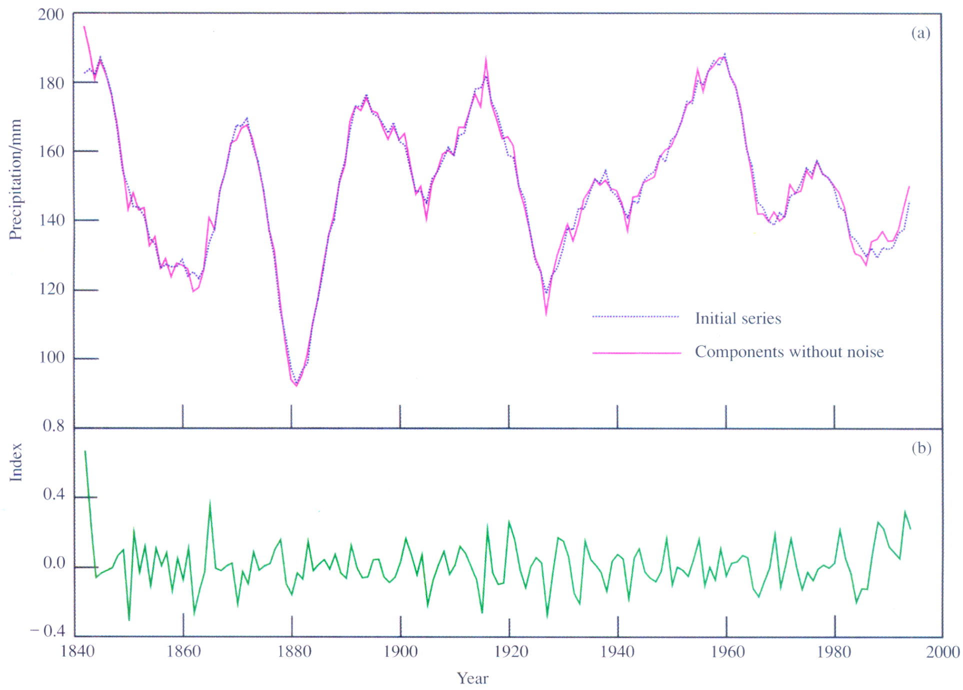

Fig. 6. (a) The result of overlapping signal (S1 + S2) and trend (T1 + N1) in the precipitation series of the Baiyinaobao. (b) Noise component, accounting for 1.6% variance of the initial series.

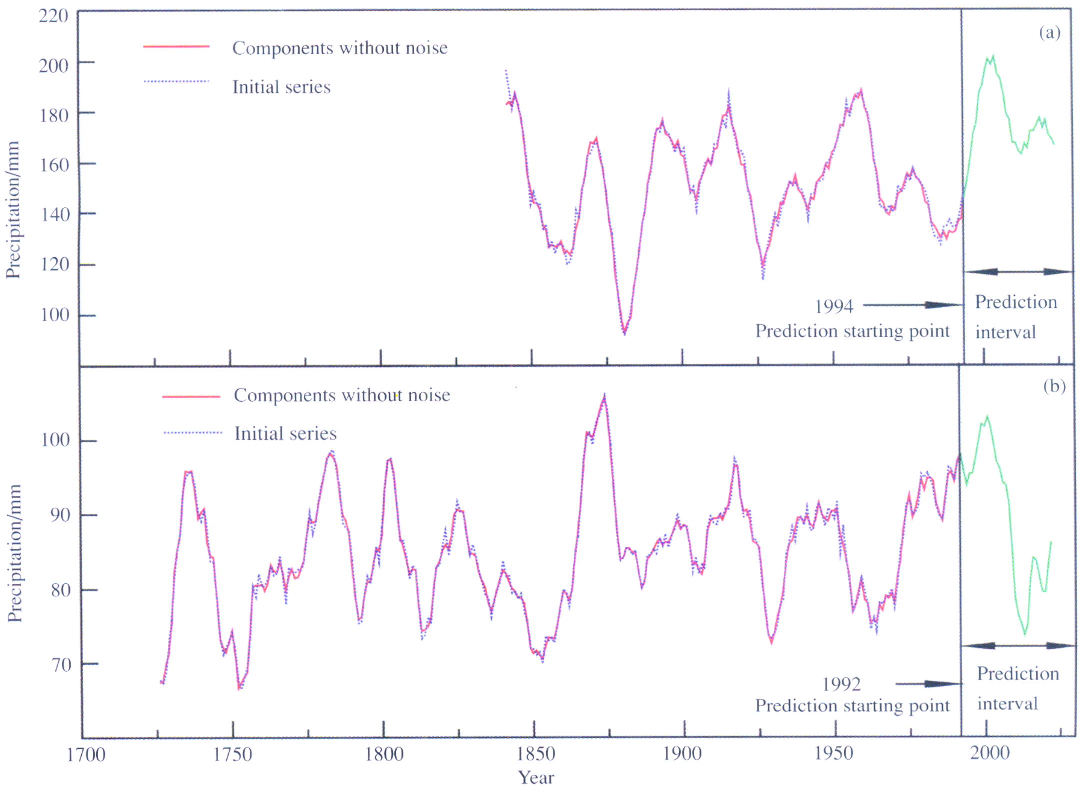

Fig. 7. The forecasting of variation tendencies of precipitation: (a) from May to July in the north Helan Mountain (1992—2022), (b) from April to early July in Baiyinaobao (1994—2024).

the lowest value in 2012—2013. Subsequently, rainfall will also increase in a sort and be higher than the average (1843—1994), but less than the 1998—2008 mean.

It is not surprising that two forecasting series display a quite similar variation tendency, since it has been shown in ref. [8] that there exists strong synchronous variation trend during their common period of the past 150 years. The seasonal precipitations in both regions increase during the period of 1992—2004, and then decrease. They both will reach to the minimum around 2012—2014. It should be noted that the predictions in this paper are based on the natural variation of the seasonal precipitation, therefore the results of the forecasting are also only for the natural variation.

Acknowledgements We thank Wang Lei, Yang Yinke for their invaluable suggestions. This work was supported by the National Natural Science Foundation of China (Grant Nos. 90211018, 40121303, 40071081 and 90102017), the National Key Basic Research Special Foundation Projects (Grant Nos. G1990434001 and 2001CCB00100), and the Knowledge Innovation Programs of the Chinese Academy of Sciences (Grant Nos. KZCX3-SW-120 and KZCX2-SW-118).

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(Received August 4, 2003; accepted December 1, 2003)