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The Decade-Scale Climatic Forecasting in China

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ABSTRACT

Described is a new technique of decade-scale climatic forecasting, presented by a combination of wavelet analysis and stochastic dynamics. The technique is also applied to diagnosing and forecasting the duration time of dry and wet climates in the decadal hierarchy of different areas in China. Results show that in the decadal hierarchy, the north, southwest, and southeast of China are areas where various kinds of frequent climate disasters appear; droughts easily occur in the north and northwest, while floods often occur in South China. Because this modeling technique is based on time series data, it can also be applied in the modeling and forecasting of such time series as hydrology, earthquakes and ecology.

Key words: wavelets, hierarchy, climatic modeling, forecasting

1. Introduction

Climate jumps, such as transformations of dry-wet, drought-flood, and cold- warm winter, often lead to climate disasters. Thus diagnosis of climate jumps is important to the country and its people. However, so far agreement has not been reached in clearly defining climate jumps. In statistical climatology, they are generally regarded as a sudden changes from one mean value to another mean value in the climate records (Zhang, 1995; Singh et al., 2002; Zhu and Chen, 2002). A climate jump is a slight discontinuity in the climate records. Obviously the mathematics are short of being precise.

Since Hasselmann (1977) first introduced some stochastic climate models, stochastic dynamics has been used to study the climatic states (Fraedrich, 1978; Kominz and Pisias, 1979), climatic change (Nicolis, 1982; Kim and North, 1991), and so on. However, it is impossible to determine the jump points by stochastic dynamics. At present, there are several common methods used to test climate jumps: low pass filter, moving t-test, Cramer's method, Yamamoto's method (Yamamoto et al., 1985; Yamamoto et al., 1986), and more. All traditional statistical diagnostic methods (Lin, 1999) and statistical forecasting models do not have any resolution power in the time-space domain and do not contain dynamic elements, so there is no way to forecast the nudging time of the climate transformation in a different hierarchy, such as dry-wet, drought-flood, cold-warm winter, and so on. Simultaneously, the dynamic forecasting of climate not only needs a lot of calculations, but also fails to forecast the jumps of the system in different hierarchies (Lin, 1993; Lin, 1999). How can the data be thoroughly used so as to establish the stochastic dynamic climate model that can forecast the jumps of the system in different hierarchies?

The authors attempt to combine the techniques of multi-resolution analysis and stochastic dynamic modeling to study the transformational characteristics and period of dry and wet climates in different areas of China and to make dynamic forecasts about future climates of dry or wet periods. The former is used to determine the level (time scale) and the jump point of the system, while the latter, based on the jump points and periodic property determined by the former, sets up a dynamic forecasting model that can describe the nudging time of dry and wet climate on this hierarchy and in this area.

2. Modeling principle and model

2.1 *Modeling principle*

It is known that the transformation of MHAT wavelets (Mayer, 1992) of any time series of $f_i(x)(i =$

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$1, 2, \ldots, n)$ is

$$F[f(x)] = a^2 \frac{d^2}{dx^2}(f * g_a), \tag{1}$$

$$g_a = g(x/a)/a^{1/2} . \tag{2}$$

Here, g is the MHAT wavelet, a is the flexible scale, and " * " is the convolution operation.

$F[f(x)]$ can be regarded as the second-step derivative of $f(x)$ for x after the smoothing of g_a, so its zero point (or the flex point in the mathematical sense) is the jump point of the system. That means that MHAT wavelets provide us with a diagnostic method of jump points with mathematical implications.

If we use $r_1, r_2, \ldots, r_n$ to stand for the time series of annual precipitation at one station, and use $R_j (j = 1, 2 \ldots)$ to stand for a new series made up of the mean value with certain common features in one part of the original series $\{r_i,\ i = 1, 2, \ldots, n\}$, then the hierarchy of the system described by the series $\{R_j, j = 1, 2, \ldots\}$ is higher than that described by the series of $\{r_i, i = 1, 2, \ldots, n\}$. Suppose the series $\{r_i, i = 1, 2, \ldots, n\}$ corresponds to the yearly level, while the series $\{R_j, j = 1, 2, \ldots\}$ corresponds to the decadal-century level. Since the property of the high hierarchy determines the characteristics of attractors or the thermodynamic branch of the low level in the system, the rule and characteristics of the system $\{R_j, j = 1, 2, \ldots\}$ can be determined qualitatively by examining some points in the series of $\{r_i, i = 1, 2, \ldots, n\}$.

Suppose the beginning and ending year of one (precipitation) time series is, respectively, a and b, while k is the time (year) corresponding to the jump point diagnosed by the MHAT wavelet (it is presumed here that there is only one jump point and later, the situation with many jump points will be discussed). Then it may held that R_1 and R_3, the anomaly average of annual precipitation before (from year a to year k) and after (from year k to year b) the jump point are two stable states (wet state and dry state) on the high hierarchy (decadal-century scale), while the annual practical precipitation r_i fluctuates around some stable state (R_1 or R_3) $r_i = R_1 + p$ or $r_i = R_3 + p$. Here p is the "disturbance" decided by all the factors (generalized force) concerning this hierarchy (yearly scale) and low hierarchy (monthly or seasonal scale) (For the high level, all the effects of the low level can be regarded as disturbance). R_1 and R_3 are two equilibrium states of the high hierarchy and can be worked out from the following formula:

$$R_1 = \frac{1}{k-a} \sum_{i=1}^{c-1} (r_i - \overline{R}) ,$$

$$R_3 = \frac{1}{b-k+1} \sum_{i=c}^{n} (r_i - \overline{R}) . \tag{3}$$

Here $\overline{R} = 1/(b-a+1) \sum_i r_i$ is the mean value, and c is the serial number of the original series as it corresponds to the jump point which will be determined by the wavelet analysis.

If there are many jump points on a certain level, or there are many wet periods and many dry periods on this level, then R_1 and R_3 should, respectively, be the mean value of many wet periods and many dry periods obtained from formula (3).

Since it is a structure of double stable states, and there must exist an unstable state, R_2, between the two stationary states, when the effect of the low level is not taken into consideration, the simplest form of the potential function, u, to describe the climate feature and rule on this hierarchy (decade-century level) should be a 4th power function about precipitation, while the corresponding generalized force $f = -u' = -du/dR$ is a 3rd power function. Namely

$$\frac{dR}{d\tau} = -R^3 + \lambda_1 R^2 - \lambda_2 R + \lambda_3 = f(R) . \tag{4}$$

Here, τ is no-scale time and R is the precipitation of the high (decadal) hierarchy. From the steady-state solution of formula (4), the following parametric function can be obtained:

$$\begin{cases} \lambda_1 = R_1 + R_2 + R_3 , \\ \lambda_2 = R_1 R_2 + R_1 R_3 + R_2 R_3 , \\ \lambda_3 = R_1 R_2 R_3 . \end{cases} \tag{5}$$

If we consider the disturbance of such factors (or the generalized force) as the characteristic hierarchy (yearly scale) and low hierarchy (monthly, seasonal scale) on the decadal-century hierarchy, then the disturbance term should be added to formula (4), thus giving the stochastic dynamical equation describing the precipitation change (or any climate variable) on the decadal-century level:

$$\frac{dR}{d\tau} = -R^3 + \lambda_1 R^2 - \lambda_2 R + \lambda_3 + F(\tau) , \tag{6}$$

$$\langle F(\tau) \rangle = 0 ,$$

$$\langle F(\tau_1) F(\tau_2) \rangle = \varepsilon^2 \delta(\tau_1 - \tau_2) . \tag{7}$$

Here, τ is no-scaling time (to ensure the coefficient of the term with third power is unitless), $F(\tau)$ is the disturbing force, ε^2 is a constant describing the disturbing intensity of random r; and angle brackets $\langle\ \rangle$

stand for the statistical mean value (here and in the following cases).

2.2 *Determination of parameters*

The equation group (6)–(7) has only three equations, but four unknowns $(R_2, \lambda_1, \lambda_2, \lambda_3)$ and moreover, there exists an unknown parameter ε in Eq.(7). Therefore, two relevant auxiliary equations should be obtained.

The Forkker-Planck equation corresponding to formula (6) is

$$\begin{aligned}\frac{\partial P}{\partial \tau} &= \frac{\partial}{\partial R}(R^3 - \lambda_1 R^2 + \lambda_2 R - \lambda_3)P + \frac{\varepsilon^2}{2}\frac{\partial^2 P}{\partial R^2} \\ &= \frac{\partial}{\partial R}(u'P) + \frac{\varepsilon^2}{2}\frac{\partial^2 P}{\partial R^2} \,.\end{aligned} \tag{8}$$

Here, $u' = -f(R) = R^3 - \lambda_1 R^2 + \lambda_2 R - \lambda_3$.

Multiplying both sides of formula (8) by R^2, and performing an integration we have

$$\frac{1}{2}\frac{d\langle R^2\rangle}{d\tau} = -\langle u'R\rangle + \frac{\varepsilon^2}{2} \,. \tag{9}$$

Suppose

$R = \overline{R_{0j}} + \delta R,\ \overline{R_{0j}} = \overline{R_{01}}$, or $\overline{R_{03}}$, $|\ \delta R/\overline{R_{0j}}\ | \ll 1$.

When $\overline{R_{0j}} = \overline{R_{01}}$, we have

$$\frac{1}{2}\frac{d\langle \delta R^2\rangle_{\overline{R_{01}}}}{d\tau} = -u'_{\overline{R_{01}}}\langle \delta R^2\rangle_{\overline{R_{01}}} + \frac{\varepsilon^2}{2} \,. \tag{10–1}$$

When $\overline{R_{0j}} = \overline{R_{03}}$, we have

$$\frac{1}{2}\frac{d\langle \delta R^2\rangle_{\overline{R_{03}}}}{d\tau} = -u'_{\overline{R_{03}}}\langle \delta R^2\rangle_{\overline{R_{03}}} + \frac{\varepsilon^2}{2} \,. \tag{10–2}$$

The steady states of (10–1) and (10–2) are

$$\langle \delta R^2\rangle_{\overline{R_{01}}} = \frac{\varepsilon^2}{2u''_{\overline{R_{01}}}} \,, \tag{11}$$

$$\langle \delta R^2\rangle_{\overline{R_{03}}} = \frac{\varepsilon^2}{2u''_{\overline{R_{03}}}} \,. \tag{12}$$

From the data, the variance of R_1 and R_3 are obtained by

$$\langle \delta R^2\rangle_{\overline{R_{01}}} = S_1 = \frac{1}{k-a}\sum_{i=1}^{c-1}(r_i - \overline{R})^2 \,, \tag{13}$$

$$\langle \delta R^2\rangle_{\overline{R_{03}}} = S_3 = \frac{1}{b-k+1}\sum_{i=c}^{n}(r_i - \overline{R})^2 \,. \tag{14}$$

Working out Eqs.(5), (13) and (14), and getting the five unknowns $(R_2, \lambda_1, \lambda_2, \lambda_3, \varepsilon^2)$ of the closed equation group (5 equations, 5 unknowns), we put the result into equation (5). Then the dynamic equation of the high level (decadal-century) of this climate variable (precipitation) is obtained.

2.3 *No-scaling time period*

The mean jump time, with no scale between dry-wet states of the stochastic dynamical system established in the previous part, will be decided by the accompanying equation of the Forkker-Planck equation:

$$f(R, \lambda_i)\frac{d\tau}{dR} + \frac{1}{2}\varepsilon^2\frac{d^2\tau}{dR^2} = -1 \,. \tag{15}$$

Suppose $R_3 < R_2 < R_1$, then R_1 and R_3 are the respective wet and dry climate states. The mean time of the system jumping from R_1 (wet period) to R_2 (flex point) is determined by the following boundary conditions:

$$R_1 \to R_2 :\ R = \infty,\ \frac{d\tau}{dR} = 0;\ R = R_2,\ \tau = 0 \,. \tag{16}$$

Similarly, the mean time of the system jumping from R_3 (dry period) to R_2 (flex point) is decided by the following boundary conditions:

$$R_3 \to R_2 :\ \ R = -\infty,\ \ \frac{d\tau}{dR} = 0;\ \ R = R_2,\ \ \tau = 0 \,. \tag{17}$$

Using the Rung-Kutta method to numerically integrate (15), the no-scaling time $\tau_{\rm w}$ required in the transition from the wet period to the jump point and $\tau_{\rm d}$, the no-scaling time required in the transition from the dry period to the jump point, can be worked out respectively from condition (15) and (17). Namely, the no-scaling nudging time of the wet period and dry period is respectively $\tau_{\rm w}$ and $\tau_{\rm d}$.

2.4 *Dry-wet Transition period*

According to the dynamical equation (4) with no-scaling time, the linearized equation of the system around one stationary state $R_i(R_1$ or $R_3)(R = R_i + \delta R,\ R_i \ll 1)$ is:

$$\frac{d(\delta R)}{d\tau} = -u''(R_i)\delta R \,. \tag{18}$$

Suppose the scale of the time is

$$t = \tau/\rho \,, \tag{19}$$

then

$$\frac{d(\delta R)}{dt} = -\rho u''(R_i)\delta R \,. \tag{20}$$

From formula (20) it can be seen that $\rho u''(R_i)$ is the recurring nudging time. If the mean period of this hierarchy is T, then it can be approximately regarded as

$$T \approx 1/\rho u''(R_i) \,.$$

So

$$\rho = \frac{1}{u''(R_i)T} = \frac{1}{(3R_i^2 - 2\lambda_1 R_i + \lambda_2)T} \,. \tag{21}$$

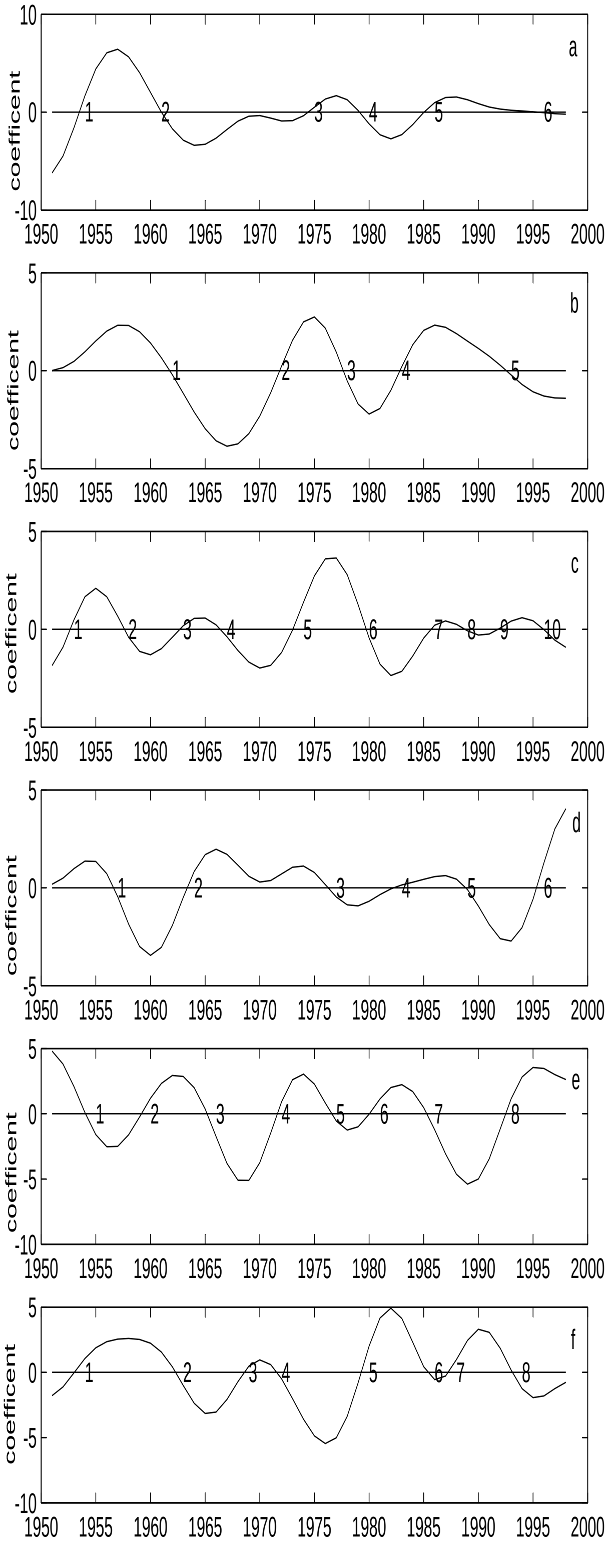

Fig. 1. The curves of wavelet transformation of precipitation with the scale of 16 years of the six biggest cities of China (a), (b), (c), (d), (e), and (f) respectively corresponds to Beijing, Shanghai, Tianjin, Chongqing, Guangzhou, and Wuhan.

On the same hierarchy, the value of ρ, obviously, should be taken as the mean value of R_1 and R_3 respectively. After determining the mean period T of all the levels of the wavelet translations, ρ can be worked out, and from formula (19), the nudging time of the whole wet period and dry period can be obtained:

$$t_{\rm w} = 2\tau_{\rm w}/\rho, \text{ and } t_{\rm d} = 2\tau_{\rm d}/\rho \,. \tag{22}$$

3. Forecasting of the transformational time of dry-wet climate of the six biggest cities in China

Wavelet transformation has a so-called boundary effect (Lin, 1999) that will lead to the distortion of wavelet coefficients corresponding to the beginning and end of the data. This boundary effect will become more apparent with the increase of the level. In order to study the jumps of the decadal hierarchy, the boundary effect should first be eliminated. Here, the method of symmetric extension (Lin, 1999) is adopted to give boundary treatment to the precipitation data of the six biggest cities of China, Beijing, Shanghai, Tianjin, Chongqing, Guangzhou, and Wuhan stations from 1951 to 1995 to eliminate the boundary effect caused by wavelet transformation. If $\{r_i, i = 1, 2, \ldots, n;\ n = 45\}$ is the annual precipitation series of one station, then the two sides of the series $\{r_i, i = 1, 2, \ldots, n;\ n = 45\}$ will be extended to construct the following new series and the extended part will be removed after the wavelet transformation. Namely,

$$r_i = \begin{cases} r_{1-i}\,, & i = 0, -1, -2, \ldots, n-1 \\ r_i\,, & i = 1, 2, 3, \ldots, n \\ r_{2n+1-i}\,, & i = n+1\,, n+2, \ldots, 2n \end{cases} \tag{23}$$

where n is the length of the data.

Let the flexible coefficient of the wavelet transformation be 16 (years), which represents the decadal scale. After the MHAT wavelet transforms the precipitation data from 1951–1995 of these stations, the curves of the wavelet coefficients with the scale of 16 years can be obtained, as shown in Fig. 1.

Figure 1 shows that the jump points in the curves of the wavelet transformation in the decadal hierarchy of the different cities and T, the mean periods, are different. The exact distribution is shown in Table 1.

From Fig. 1 and Table 1, we see that on the level of 16 years, the stations in these cities have a great discrepancy in climate change. There are obvious differences, either in the phase or in the amplitude. The climate changes most frequently in Tianjin whose mean period is 9 years. The climate changes least frequently

Table 1. The jump points and the mean period T in decadal hierarchy in the six biggest cities in China

	1st	2nd	3rd	4th	5th	6th	7th	8th	9th	T
Beijing	1954	1960	1974	1979	1985	1995				16
Shanghai	1962	1971	1977	1982	1992					15
Tianjin	1953	1957	1962	1966	1973	1979	1985	1988	1991	9
Chongqing	1957	1963	1976	1982	1988	1995				15
Guangzhou	1955	1959	1965	1971	1976	1980	1985	1992		10
Wuhan	1954	1962	1971	1979	1985	1987	1993			11

Table 2. The two stable states of the six biggest cities in China in the decadal hierarchy

	R_1 (wet state)	R_3 (dry state)
Beijing	0.0845	-0.0231
Shanghai	0.0570	-0.1161
Tianjin	0.0672	-0.0417
Chongqing	0.0340	-0.0609
Guangzhou	0.0840	-0.1343
Wuhan	0.1325	-0.1804

in Shanghai whose dry-wet mean period is as long as 15 years.

From formulas (3)–(5), the two stationary states (anomalies) of the precipitation on the decadal hierarchy in the six biggest cities in China (or the respective average of the wet and dry state) can be worked out, as shown in Table 2.

From Table 2 it can be seen that in the six biggest cities of China, the Chongqing wet period has the smallest relative anomaly precipitation (relative to annual mean precipitation) while Wuhan has the largest relative anomaly precipitation. In the dry period, the smallest relative precipitation lies in Beijing.

From (5)–(14) the parameters $R_2, \lambda_1, \lambda_2, \lambda_3, \varepsilon^2$ in the dynamic equation of precipitation in the decadl hierarchy in the six biggest cities of China can be worked out, as shown in Table 3.

From formulas (15)–(22), we can get τ_{w} and τ_{d}, the no-scaling duration times of the dry and wet periods in different areas of the west, ρ_1 and ρ_3, along with the transformational coefficient, and t_{w} and t_{d}, the real duration times of the dry and wet periods, as shown in Table 4.

Table 4 shows the following. (1) Except in Chongqing, the remaining five biggest cities in China have a dry period that lasts much longer than the wet period, which demonstrates the universality of droughts in the cities of China. (2) In the decadal hierarchy, of all the six biggest cities in China, Wuhan has the longest dry period (21.5 years) while Tianjin has the shortest dry period (6.4 years), while Chongqing has the longest wet period (9 years) and Tianjin has the shortest wet period (4.6 years).

Table 3. The parameters of the dynamic equations of precipitation forecasting of the six biggest cities in China in the decadal hierarchy

	R_2	λ_1	λ_2	λ_3	ε^2
Beijing	0.025997	0.02819	-0.00690	-0.00018	0.00100143
Shanghai	-0.001270	-0.06020	-0.00656	0.00001	0.0011749
Tianjin	-0.020752	0.04631	-0.00227	0.00006	0.00024966
Chongqing	-0.017953	-0.04479	-0.00159	-0.00004	0.00017056
Guangzhou	-0.002147	-0.07070	-0.01013	0.00024	0.00399924
Wuhan	0.046203	-0.00167	-0.02611	-0.00110	0.00539602

Table 4. The forecasting of the duration times of the dry and wet climates of the six biggest cities in China in the decadal hierarchy

	τ_{w}	τ_{d}	ρ_1	ρ_3	t_{w} (year)	t_{d} (year)
Beijing	19.126	38.863	6.4018	3.4587	7.759	15.764
Shanghai	16.746	36.842	6.6409	3.3454	6.707	14.757
Tianjin	44.098	61.593	21.959	16.349	4.604	6.431
Chongqing	67.755	54.654	13.514	16.371	9.069	7.311
Guangzhou	12.689	13.553	4.3645	4.1189	5.982	6.390
Wuhan	7.670	24.992	3.3670	1.2824	6.599	21.501

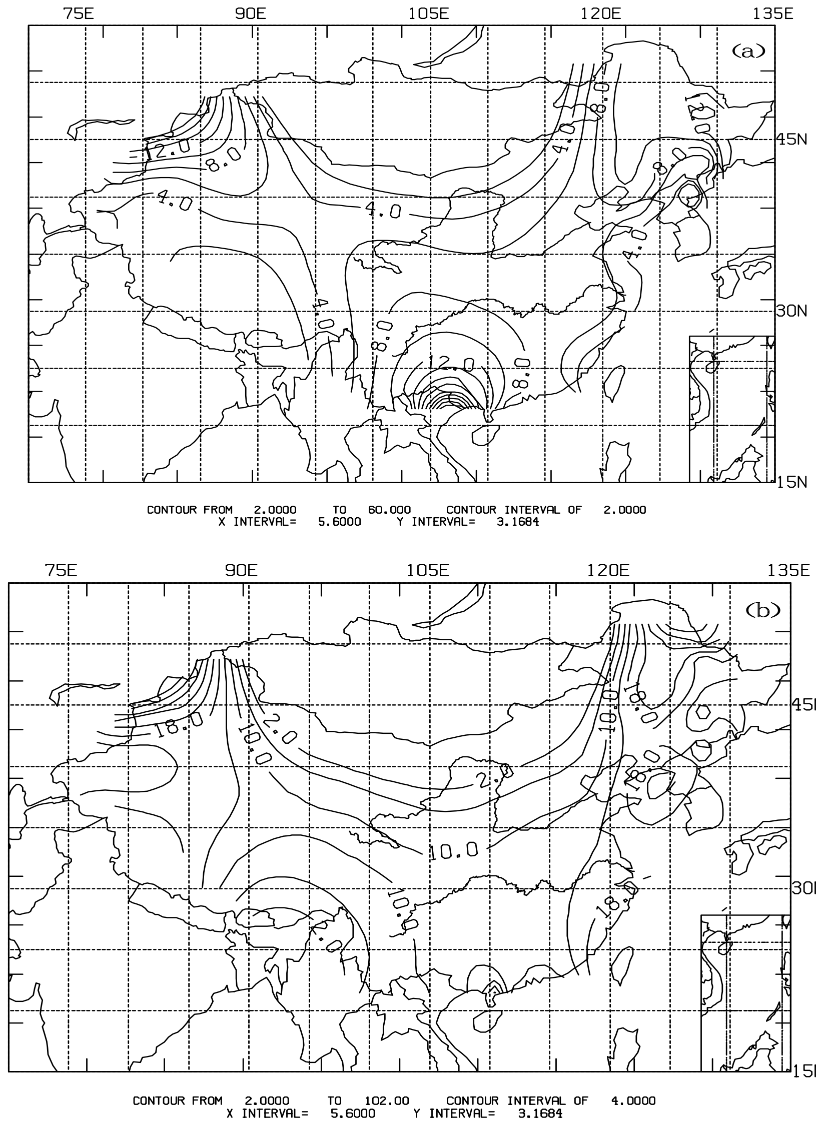

Fig. 2. The isotimic distribution of the nudging time of the wet period (a) and the dry period (b) in China.

From Table 1 it can be known that Beijing, Shanghai, Tianjin and Wuhan, respectively, enter the dry period in 1995, 1992, 1991, and 1993, while Chongqing and Guangzhou, respectively, enter the wet period in 1995 and 1992. Combining this with Table 4 anticipates that the time when Beijing, Shanghai, Tianjin, and Wuhan would enter the next wet period is, respectively, 2011, 2007, 2011, 1997, and 2014, and the time that Chongqing and Guangzhou would enter the next dry period is, respectively, 2004 and 1998.

4. Distribution of duration time of dry and wet climates in China

According to the precipitation data of 160 stations in China, modeling and forecasting are carried out. That is, by taking the above method, a dynamic equation is set up, based on the data of every station (there are altogether 160 dynamical equations with different coefficients), and the dynamic equation is used to forecast the nudging time of the dry and wet climate in this area. Figure 2 is the isoline distribution obtained from the forecasting value of the 160 dynamical equations.

From Fig. 2a, it can be seen that in the decadal hierarchy, the distribution of the duration time of the wet period in China displays the following features. (1) It is long in the south and short in the north, long in the northeast and short in the northwest, and the same follows in the southeast and southwest of China.

(2) The lines of the isotimic distribution of the nudging time of the wet period in the south are more concentrated than those in the north. These lines partially explain the fact that Northwest and North China (not including the northeast) are short of water, while flood often happens in the south. From Fig. 2b, it can be seen that the distribution of the duration time of the dry period in China has the following features. (1) The northeast and northwest have longer dry periods, and the dry period in the middle area of China is only shorter than those two areas. (2) The nudging time of the dry period is longer than the nudging time of the wet period in the north. Combining (a) and (b) in Fig. 2, we also find that in the decadal scale, the climate period in the south of China is obviously longer than that in the north of China, and the climate period in the northeast and northwest of China is obviously longer than that in southwest and southeast of China. This demonstrates that in China, the climate changes more frequently in the north than in the south, and more frequently in the northeast than in the northwest. The frequent change of climate means that climate disasters will appear very frequently.

5. Conclusion

The theory of climate hierarchy (Lin, 1993), the modeling technique of the equilibrium state, and the technique of wavelet analysis (Lin, 1999) are combined to raise a set of statistical-dynamical modeling techniques to describe the precipitation change on the decadal scale in China. The precipitation data of 160 stations in China are used to set up 160 corresponding dynamical models of dry and wet climate on the decadal scale. After dynamically forecasting the nudging time of dry and wet climate in different areas (160 stations) of China, it can be found from the decadal-hierarchy, the north, southwest, and southeast areas of China are the areas where all kinds of climate disasters appear frequently; drought easily happens in the northwest and north (not including the northeast); flood often occurs in the south of China.

It is necessary to point out that the statistical-dynamic modeling technique raised in this paper can be taken not only to establish the dynamical climate model of precipitation and temperature on the decadal scale, but also to set up all kinds of dynamical climate models in the scales of longer time. From the perspective of pure technique, the most ideal time is ten years or dozens of years. Theoretically, the less jump points, the better the forecasting result; whereas with more jump points, the forecasting result is worse. On the other hand, this technique is about the modeling on the basis of time series, so it can also be applied in the modeling and forecasting of such time series as hydrology, earthquakes, and ecology.

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中国“代”尺度气候预测

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摘　要

将子波分析技术与随机动力学相结合，提出了突变点数建模代尺度气候预测新技术—突变点数建模技术，并将该技术应用于中国不同地区代尺度的干湿驰豫时间的预报。研究结果表明，在代尺度上，我国北方、西南和东南气候灾害频繁，南方多涝，西北和北方（不包括东北）则多旱。由于该技术是关于时间序列建模的，故可以应用到水文、地震、生态等领域有关的建模和预测。

关键词：子波，层次，气候建模，预测