Spatio-Temporal Correlation Analysis of Global Temperature Based on the Correlation Matrix Theory*

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ABSTRACT

Based on the NCEP/NCAR reanalysis daily mean temperature data from 1948 to 2005 and random
time series of the same size, temperature correlation matrixes (TCMs) and random correlation matrixes
(RCMs) are constructed and compared. The results show that there are meaningful true correlations as well
as correlation “noises” in the TCMs. The true correlations contain short range correlations (SRCs) among
temperature series of neighboring grid points as well as long range correlations (LRCs) among temperature
series of different regions, such as the El Niño area and the warm pool areas of the Pacific, the Indian Ocean,
the Atlantic, etc. At different time scales, these two kinds of correlations show different features: at 1–10-day
scale, SRCs are more important than LRCs; while at 15-day-or-more scale, the importance of SRCs and
LRCs decreases and increases respectively, compared with the case of 1–10-day scale. It is found from the
analyses of eigenvalues and eigenvectors of TCMs and corresponding RCMs that most correlation information
is contained in several eigenvectors of TCMs with relatively larger eigenvalues, and the projections of global
temperature series onto these eigenvectors are able to reflect the overall characteristics of global temperature
changes to some extent. Besides, the correlation coefficients (CCs) of grid point temperature series show
are significantly higher than average while that over the periods 1978–1982 and 1991–1996 are opposite,
suggesting a distinctive oscillation of quasi-10–20 yr. Spatially, the CCs at 1- and 15-day scales both show
band-like zonal distributions; the zonally averaged CCs at 1-day scale display a better latitudinal symmetry,
while they are relatively worse at 15-day scale because of sea-land contrast of the Northern and Southern
Hemisphere. However, the meridionally averaged CCs at 15-day scale display a longitudinal quasi-symmetry.

Key words: matrix theory, correlation coefficient, eigenvalue, eigenvector, spatial distribution

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1. Introduction

The global climate system is a highly nonlinear,
multi-hierarchical, and forced-dissipative complex sys-
tem. Under the effect of solar radiation and atmo-
spheric general circulation, a series of physical pro-
cesses and complicated nonlinear interactions arise
within it, and various components of the system are
closely connected, forming an entirety through ex-
changes of matter and energy (Liu and Liu, 1999; Shi,
2005; Dai et al., 2005). Significant progress in cli-
mate system studies has been made by researchers all
over the world (Xiao and Li, 2007a, b; Feng et al.,
2005; Wang, 2005a, b), especially in the past decade.
It has been recognized that climate system is multi-
hierarchical and non-stationary, and local climate is
impacted by the global climate change, and vice versa.
According to spatial distance, connections among re-
gional climate sub-systems may be divided into two
major categories: short range connection (SRC) and

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long range connection (LRC). The LRC refers to teleconnections, such as the Northern Atlantic Oscillation (NAO), the Northern Pacific Oscillation (NPO), the Southern Oscillation (SO) (Walker and Bliss, 1932; Keppenne and Ghil, 1992; Lamb and Peppler, 1987), etc. Because the atmosphere is a compressible fluid, if the whole atmospheric system is viewed as a complex system made up of small regional basic units, then there are exchanges of energy, momentum, and thermodynamic entropy among them, i.e., the SRCs (Hu, 2002).

Understanding of short-, mid-, and long-term climate predictions has been obviously improved since the 1960s based on many research works, especially Charney et al. (1966), Lorenz (1969a,b), and Smagorinsky (1969). Chou and Xu (2001) commented on defects of current numerical prediction of short-term climate, presented four challenging problems, and pointed out the perspective and direction of short-term climate prediction. Hong et al. (2006) made mid- and long-term forecasts of subtropical high activities by time integration of the nonlinear prediction model and the spatio-temporal reconstruction of EOF analysis. Ding and Li (2008) recently investigated the spatio-temporal distributive characters of predictabilities of temperature, height and zonal wind fields based on the non-linear error growth theory. Up to now, studies on multi-scale characters of changes of climate element correlations are rarely performed.

To describe and forecast climate states on various spatio-temporal scales, it is necessary to systematically study the correlations among subsystems of the climate system using adequate mathematical statistics and dynamic methods. However, studies in this aspect are mostly limited to the interactions and connections of a few regional climate subsystems; very few studies focus on the inter-relations of climate subsystems by viewing climate system as a giant and complex network. Owing to the inherent complexity of climate system, investigations of the inherent relations among subsystems from the global point of view help to better understand the basic structure of climate system, and to better reveal its inherent properties. Based on the NCEP/NCAR reanalysis daily mean temperature data, this paper explores links and differences between global temperature series correlations and stochastic series correlations, investigates the eigen-modes which most distinctively impact correlations of global grid point temperature series, and discusses multi-scale characters of the spatio-temporal evolution of global temperature series.

2. Data and method

2.1 Data

The NCEP/NCAR reanalysis daily surface temperature data (5° × 5°) from 1948 to 2005 (Kistler et al., 2001) \( [T_i(t), i = 1, \ldots, 2592; t = 1, \ldots, 21170] \) were used in this paper. The standard daily mean temperature series \( [T_i(t), i = 1, \ldots, 2592; t = 1, \ldots, 365] \) were calculated using the above reanalysis temperature data from 1971 to 2000 \( [T_i(k), i = 1, \ldots, 2592; k = 1, \ldots, 10950] \):

\[
T_i(t) = \frac{1}{30} \sum_{\text{mod}(k, 365) = l} T_i(k). \tag{1}
\]

To filter out seasonal oscillation signal:

\[
T'_i(t) = T_i(\text{mod}(t, 365)) - \bar{T}_i(l), \tag{2}
\]

then the series \( [T'_i(t), i = 1, \ldots, 2592; t = 1, \ldots, 21170] \) were used to construct temperature correlation matrices (TCMs) in this paper.

2.2 The correlation matrix theory

The main procedure of the correlation matrix theory is as follows: the standardization of original data \( [X_i(t), i = 1, \ldots, M; t = 1, \ldots, N] \) were first performed:

\[
X'_i(t) = \frac{X_i(t) - \langle X_i \rangle}{\sigma_i}, \tag{3}
\]

where \( \langle X_i \rangle \) is the mean value of \( X_i(t) \), \( \sigma_i = \sqrt{\langle X_i^2 \rangle - \langle X_i \rangle^2} \). The mean of \( X'_i(t) \) is 0, and its standard deviation is 1. Then the \((ij)\)th element of the correlation matrix \( X \) (Muirhead, 1982) is:

\[
X_{ij} = \frac{1}{N} \sum_{t=1}^{N} X'_i(t)X'_j(t) \tag{4}
\]

\((i = 1, \ldots, M; j = 1, \ldots, M)\).
where \(-1 \leq X_{ij} \leq 1\). If \(X_{ij} = 1\), it indicates a completely positive correlation, while \(X_{ij} = -1\) denotes a completely negative correlation, and \(X_{ij} = 0\) means no correlation. The eigenvalue \(\lambda_i\) and eigenvector \(v_i\) of \(X\) have the following relation:

\[
Xv_i = \lambda_i v_i \quad (i = 1, \ldots, N).
\]

The probability distribution of eigenvalues directly reflects the correlation extent of the original data (Muller et al., 2005).

There are two limitations in the analysis of the correlation matrix \(X\) constructed with climatic elements. First, the climatic background changes with time, and the correlations between climatic elements at two arbitrary grid points are changeable. Second, there always exist some false correlations due to the limitation of data size. How can we determine if the correlations between climatic elements at certain grid points over a certain period of time are true or not? To address this problem, random correlation matrices (RCMs) constructed with mutually independent random time series are used to determine the ineffective correlation value range. By doing so, we discuss separately two aspects of TCMs: the statistical properties consistent with and deviated from that of RCMs.

3. Results

3.1 Probability distributions of Correlation Coefficients

A TCM \(T\) was constructed by correlation coefficients (CCs) calculated from \(T_i^s(t)\) \((i = 1, \ldots, 2592; t = 1, \ldots, 21170)\), and a random function was used to create random time series with the same size, then the RCM \(R\) was constructed. To obtain the scale characters of climate change, running means of 5, 10, \ldots, and 30 days were applied to the original temperature series and random time series respectively, then TCMs and RCMs corresponding to different time scales were generated. Figures 1a-c show parts of \(R\) (1-day scale) and \(T\) (1- and 15-day scales). Obviously, the arrangement of CCs of \(R\) is chaotic, and the values are very small; the CCs of \(T\) at 1-day scale decrease from the diagonal towards its two sides and the value range is much more larger than \(R\); the situation of \(T\) at 15-day scale is similar to that at 1-day scale except the CCs are overall larger.

Figure 2a shows the probability distributions of CCs of RCMs and TCMs at 1-, 5-, 15-, and 30-day scales. The probability distribution of CCs of \(R\), i.e., \(P(R_{ij})\) accords well with the Gaussian symmetric distribution, with a mean of 0 and a very narrow value range \([-0.02, 0.02]\), indicating that there are few meaningful relations between random series but meaningless correlation “noises”. The probability distribution of CCs of \(T\), i.e., \(P(T_{ij})\) is to a certain extent different from \(P(R_{ij})\). Although \(P(T_{ij})\) at 1-, 5-, 15-, and 30-day scales show large peaks within the value range \([-0.02, 0.02]\) like \(P(R_{ij})\), they also show certain distributions in the relatively wider ranges \([-1.0, -0.02]\] and \([0.02, 1.0]\). Furthermore, when the 1-day scale temperature series are shuffled, the probability distribution of CCs degenerates to a Gaussian like distribution. The shuffling procedure was repeated for TCMs at 5-, 15-, and 30-day scales, and the results were the same as those at 1-day scale. This indicates
that there must be meaningful true correlations between grid point temperature series, which might be a manifestation of the synchronous response of grid point temperature to global climate background. Besides, correlation "noises" also exist in TCMs, and it must be deleted before the analyses of correlations of grid point temperature.

It is observed from Fig. 2b that along with the increase of time scale, the average value of CCs larger than 0.3 (C1) decreases, but the average value of all the CCs (C2) increases, and both changes obviously slow down (the slopes of C1 and C2 become gentle) when the scale is greater than 15 days. The reason for this may be that SRCs between neighboring or next-neighboring grid points dominates the correlation at 1–10-day scale, while most of LRCs between distant grid points are correlation "noises". A relatively larger scale is able to weaken the impact of "noises" and external forcing, and the regional synchronization of temperature change is enhanced, so the portion of LRCs increases at 15-day-or-longer scale, and the overall average CC increases.

To examine the importance of LRC and SRC at different time scales, accumulative distribution of the pairs of correlative grid points was calculated using the following procedure. We took a certain grid point \((x_i, y_i)\) as a center \((x_i = \frac{Lat_i - 87.5}{5}, y_i = \frac{Lon_i}{5})\), where \(Lat_i\) is the latitude of point \(i\), and \(Lon_i\) is the longitude of point \(i\). The distance of grid point \((x_j, y_j)\) to the center is \(d_{ij} = \sqrt{(x_j - x_i)^2 + (y_j - y_i)^2}\) and the CC between them is noted as \(C_{ij}\). We set a criterion \(C_0 = 0.3\), and reckoned the number \(N_{ij}(d)\) of the pairs of correlative grid points whose distance is \(d\) and the corresponding \(C_{ij} > C_0\), in the cases of 1- and 15-day scales, respectively. The same procedure were applied for all grid points, and the accumulative distribution of the pairs of correlative points versus distance \(d\) was obtained by adding up all \(N_{ij}(d)\):

\[
N(d) = \sum_{i=1}^{M} \sum_{j=1}^{M} N_{ij}(d).
\]

Similar calculations were repeated under conditions of \(C_0 = 0.2, 0.4, 0.5 \ldots\), and the results obtained are approximately the same. It can be seen from Fig. 3 that the accumulative pairs of correlative points obey the dual power law distribution:

\[
P(d) = \begin{cases} 
Ad^\lambda, & d < d_0, \\
Bd^\gamma, & d > d_0,
\end{cases}
\]

where \(A, B\) are constants, and \(\lambda, \gamma\) are power law exponents, i.e., there are two accumulative distributions of the pairs of correlative points for 1- and 15-day scales, respectively. In the case of 1-day scale, \(d_0 \approx 4, \lambda = 1.13 \pm 0.07\), when \(d < 4\); and \(\lambda = 0.17 \pm 0.01\)
Fig. 3. Accumulative distribution of the pairs of correlative points plotted in logarithm coordinates. The abscissa is distance between two grid points, and the ordinate is the accumulative pairs of correlative points.

when \( d > 4 \); while in the case of 15-day scale, \( d_0 \approx 6 \), \( \lambda = 1.27 \pm 0.04 \), when \( d < 6 \); and \( \gamma = 0.30 \pm 0.01 \) when \( d > 6 \). The slope of the distributive curve becomes gentle when \( d > 4 \) in the case of 1-day scale, but it is so only when \( d > 6 \) in the case of 15-day scale, indicating that LRCs at 15-day scale increase in comparison with those at 1-day scale.

3.2 Probability distribution of matrix eigenvalue

The above discussion suggests that \( T \) to a certain extent differs from \( R \), indicating that there exist correlation “noises” as well as true correlations in \( T \). However, it is not enough for understanding properties of global temperature correlativity. We are going to further analyze eigenvalues and eigenvectors of correlation matrices below.

Figures 4a and 4b show that the probability distributions \( P(\lambda) \) of eigenvalues of TCMs at 1- and 15-day scales both display the same character: small eigenvalues densely occur, and large eigenvalues sparsely occur; the larger the eigenvalue, the sparser the occurrence. On the whole, probability distributions of eigenvalues of the TCMs at 1- and 15-day scales both conform to the power law distribution:

\[
P(\lambda) = \begin{cases} 
2.02e^{-\lambda/0.20} + 0.04, & \text{1-day scale,} \\
0.63e^{-\lambda/0.18} + 0.01, & \text{15-day scale.}
\end{cases}
\]

The reason for this distributive character may be that after EOF expansion of TCM, the eigenvalues must satisfy \( \sum_{i=1}^{M} \lambda_i = M \), and major information concentrates in a few eigenvectors with relatively larger eigenvalues (see further discussion below).

Figure 4c shows the probability distribution of eigenvalues of \( R \) (the thin solid line), characters of which obviously differ from those of TCMs at the 1- and 15-day scales. Eigenvalues of \( R \) concentrate...
within a fixed range. According to existing studies (Dyson, 1971; Senguta and Mitra, 1999), for a completely random matrix, under the limitation of \( N \rightarrow \infty \) and \( M \rightarrow \infty \), \( Q = N/M \) stays constant, the theoretical probability distribution of eigenvalues is given by:

\[
P_{rm}(\lambda) = \frac{Q}{2\pi \sqrt{\lambda}} \left( \frac{\lambda_+ - \lambda}{\lambda} \right),
\]

(9)

where \( \lambda_- \leq \lambda \leq \lambda_+ \), \( \lambda_- \) and \( \lambda_+ \) are the least and largest eigenvalues, respectively (Bowick and Brezin, 1991).

\[
\lambda_{\pm} = 1 + \frac{1}{Q} \pm 2\sqrt{\frac{Q}{2}}.
\]

(10)

In this paper, \( N = 21170, M = 2592 \), therefore, \( Q = 8.17, \lambda_- = 0.42, \lambda_+ = 1.83 \), and the theoretical probability distribution of eigenvalues of \( R \), i.e., \( P_{rm}(\lambda) \) was calculated. In Fig. 4c, the probability distribution of eigenvalues of \( R \) (the thin solid line) basically conforms to the theoretical distribution \( P_{rm}(\lambda) \) (the thick solid line). Therefore, it can be inferred that the eigenvalue of \( R \) lies within \([\lambda_-; \lambda_+]\), where the eigenvalues reflect some false correlation information of the matrix. It is known from comparing Figs. 4a, 4b with 4c that the eigenvalues of TCMs at 1- and 15-day scales can be split to three regions: a small value region- region I \((-\infty; \lambda_-] \); a random correlation region- region II \([\lambda_-; \lambda_+] \); and a large value region-

Fig. 5. Probability distributions of the eigenvalues of TCMs at (a) 1- and (b) 15-day scales and (c) of RCM.
region III \([\lambda_+, \infty]\).

3.3 Probability distribution of matrix eigenvector

Differences in the eigenvalues of RCM and TCM should be reflected in the eigenelements of corresponding eigenvectors (Laloux et al., 1999). We interpret physical meanings of the eigenvalues in regions I and III with the analysis of eigenvectors below. Figures 5a-c show that the probability distributions of eigenelements of eigenvectors \(U_1, U_{2590}, \) and \(U_{2592}\) of RCM all obey the Gaussian distribution:

\[
P = A + Be^{-[2(u-0.005)/0.04]^2},
\]

where \(A\) and \(B\) are changeable constants. The probability distributions of the eigenelements of \((U_1(\lambda < \lambda_+), \text{region I})\) of TCMs at 1-day (Fig. 5d) and 15-day scales (Fig. 5g) are similar with those of RCM (Figs. 5a-c), which implicates that the eigenvalues and their corresponding eigenvectors in region I only reflect some meaningless relation "noises" of the TCMs. The probability distributions of the eigenelements of \(U_{2590}\) and \(U_{2592}\) (\(\lambda > \lambda_+, \text{region III}\)) at 1-day (Figs. 5e, 5f) and 15-day scales (Figs. 4h, 4i) to different extent deviate from the Gaussian distribution; the larger the eigenvalue, the larger the deviation.

Because eigenvectors with relatively larger eigenvalues may contain major correlation information among grid point temperature series, we analyze the possible effect of eigenvectors (regions I and III) on overall characters of global temperature change. Similar to the correlation analysis of economic series (Campbell et al., 1997; Garas and Argyrakis, 2007), we first constructed the overall mapping series of global temperature change based on the 1-day-scale TCM and the 1-day-scale grid point temperature series from 1948 to 2005:

\[
T^1(t) = \sum_{j=1}^{M} u^1_j T_j(t). \quad M = 2592, t = 1, \ldots, 21170. (12)
\]

\[
T^{2592}(t) \text{ and } T^{2592}(t) \text{ denote the mappings of global temperature change onto } U_1 \text{ and } U_{2592}, \text{ respectively. Besides, we calculated the daily global mean temperature }
\]

series \(G(t)\) over 2592 grid points:

\[
G(t) = \frac{1}{M} \sum_{i=1}^{M} T_i(t). \quad M = 2592, t = 1, \ldots, 21170. (13)
\]

Obviously, \(G(t)\) contains the overall characters of global temperature change. The standardized \(T^1(t), T^{2592}(t)\), and \(G(t)\) are plotted in Figs. 6a, 6b respectively. For 1-day scale, the CC between \(T^1(t)\) and \(G(t)\) is 0.90 (Fig. 6b), while the CC between \(T^{2592}(t)\) and \(G(t)\) is 0.90 (Fig. 6b). Similar operations are performed on 15-day scale grid point temperature series with the results shown in Figs. 6c and 6d. It is known from Fig. 6 that at both 1- and 15-day scales, the eigenvectors with the least eigenvalue contains almost no information associated with global temperature change, while the eigenvectors with the largest eigenvalue do involve the overall information of global temperature change; eigenvectors corresponding to eigenvalues of region III make more contribution to the global correlations of grid point temperature (Plerou et al., 1999).

To further confirm the above finding, we calculated the contribution \((v_i)\) of 10 eigenvectors with the largest eigenvalues in region III at 1- and 15-day scales respectively, according to Eq. (14) (Wilks, 1995), and the results are listed in Table 1:

\[
v_i = (\lambda_i / \sum_{j=1}^{m} \lambda_j) \times 100\%. \quad M = 2592. (14)
\]

Clearly, for 1-day scale, the contribution of eigenvectors with the largest eigenvalues to the correlation of global grid point temperature series is 5.14%, and the accumulative contribution of the 10 eigenvectors with the largest eigenvalues is 22.40%. In comparison with the case of 1-day scale, the contribution at 15-day scale concentrates more in a few eigenvectors with relatively larger eigenvalues. However, there is no eigenvector in \(R\) whose contribution is obviously larger.

3.4 Spatio-temporal characters of the correlativity of grid point temperature

The above analysis verifies that there are real correlations among grid point temperature series. We next take 1- and 15-day scales as examples to further
Fig. 6. Correlations between $T^1(t)$ and $G(t)$ (a, c) and $T^{2592}(t)$ and $G(t)$ (b, d) at 1-day scale (a, b) and 15-day scale (c, d).

Table 1. Contributions of the 10 eigenvectors with the largest eigenvalues of RCM and TCMs at 1- and 15-day scales to correlation of global grid point temperature series

<table>
<thead>
<tr>
<th>$\lambda_i$</th>
<th>2583</th>
<th>2584</th>
<th>2585</th>
<th>2586</th>
<th>2587</th>
<th>2588</th>
<th>2589</th>
<th>2590</th>
<th>2591</th>
<th>2592</th>
<th>Sum</th>
</tr>
</thead>
<tbody>
<tr>
<td>1-day-scale TCM</td>
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<tr>
<td>$\lambda_i$</td>
<td>30.81</td>
<td>34.36</td>
<td>37.29</td>
<td>37.87</td>
<td>43.57</td>
<td>45.01</td>
<td>50.04</td>
<td>77.67</td>
<td>81.43</td>
<td>133.41</td>
<td>–</td>
</tr>
<tr>
<td>$v_i$ (%)</td>
<td>1.19</td>
<td>1.33</td>
<td>1.44</td>
<td>1.46</td>
<td>1.68</td>
<td>1.74</td>
<td>1.93</td>
<td>3.00</td>
<td>3.14</td>
<td>5.14</td>
<td>22.40</td>
</tr>
<tr>
<td>15-day-scale TCM</td>
<td></td>
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<tr>
<td>$\lambda_i$</td>
<td>17.40</td>
<td>18.47</td>
<td>23.78</td>
<td>27.00</td>
<td>33.07</td>
<td>34.27</td>
<td>36.47</td>
<td>58.44</td>
<td>71.71</td>
<td>1835.60</td>
<td>–</td>
</tr>
<tr>
<td>$v_i$ (%)</td>
<td>0.67</td>
<td>0.71</td>
<td>0.92</td>
<td>1.04</td>
<td>1.28</td>
<td>1.32</td>
<td>1.41</td>
<td>2.25</td>
<td>2.77</td>
<td>70.81</td>
<td>83.81</td>
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<tr>
<td>RCM</td>
<td></td>
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<tr>
<td>$\lambda_i$</td>
<td>1.79</td>
<td>1.79</td>
<td>1.79</td>
<td>1.80</td>
<td>1.80</td>
<td>1.80</td>
<td>1.80</td>
<td>1.81</td>
<td>1.81</td>
<td>1.82</td>
<td>–</td>
</tr>
<tr>
<td>$v_i$ (%)</td>
<td>0.069</td>
<td>0.069</td>
<td>0.069</td>
<td>0.069</td>
<td>0.069</td>
<td>0.070</td>
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<td>0.070</td>
<td>0.070</td>
<td>0.070</td>
<td>0.695</td>
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</table>
investigate spatio-temporal characters of the correlativity of grid point temperature.

Set slide window length $win = 5$ yr, and slide step as 1 yr, calculate CCs of global grid temperature series $T_{ij}'$ within slide windows (1948–1952, 1949–1953,..., and 2001–2005), construct the correlation matrix $T'$ with $T_{ij}'$, and compute the mean value, $<T_{ij}'>$:

$$T_{ij}' = \frac{1}{win \times 365} \sum_{t=1}^{win \times 365} T_i'(t)T_j'(t),$$

$$<T_{ij}'> = \frac{1}{M(M-1)} \sum_{i=1}^{M} \sum_{j=1}^{M} T_{ij}'(i \neq j)(M = 2592).$$ (15)

The mean values of CCs of global grid temperature series within the slide windows starting from 1948 were calculated successively, and are denoted by $<T_{ij}'>$, $l = 1948, 1949,..., 2001$. Similar computations were repeated on random series and time-shuffled temperature series, and the results are plotted in Fig. 7. The mean values of CCs of random series and shuffled temperature series oscillate within a narrow range around zero, completely reflecting randomness. The mean values of CCs of grid point temperature series show different change patterns around 1977. This may reflect the abrupt change of temperature in the mid-late 1970s, which not only corresponds to the phase change of temperature variation, but also to the change in correlativity of global grid point temperature series. 1948–1977, 1987–1990, and 1999–2002 are three high correlation periods, when the correlativity among global grid point temperature is better, i.e., the regional synchronization of global temperature change is relatively better; while 1978–1982 and 1991–1996 are two low correlation periods, when the regional diversity is distinctive. Generally speaking, correlations among most grids are correlation “noises”, whose values are generally small and less changeable; the whole climate system is mostly affected by important LRCs of some crucial regions. The alternative occurrences of high and low correlation periods suggest some interdecadal oscillations. The wavelet and power spectrum analyses of temporal variations of CCs also revealed the existence of quasi-periodic oscillations of 10–20 yr.

According to Xiao and Li (2007a, b) and Feng et al. (2006), climate system has interdecadal variations and abrupt changes, during those processes some important correlations among crucial regions might change as well. To verify the above results, we also performed similar calculations at $win = 4$ yr. The computational results are similar to those at $win = 5$ yr.

The average values of CCs of each grid point with all the other grid points were calculated, with the spatial distribution plotted in Fig. 8. The spatial distributions at 1-day (Fig. 8a) and 15-day scales (Fig. 8b) both show a zonal band-like distribution, with the most significant correlation area in the equator and equatorial low latitudes. At 1-day scale (Fig. 8a), region A corresponds to the North Pacific where the correlation is anomalously small; the reason for this may be that the North Pacific is a sensitive region to global atmospheric and oceanic changes, and sea surface temperature (SST) there oscillates interdecadally and is evidently negatively correlated with the South Pacific (Mantua et al., 1997; Trenberth and Hurrell, 1994), so such a negative correlation is reflected at 1-day scale. Regions C, D, and E correspond to the western Pacific warm pool (Li et al., 1998), the Indian Ocean warm pool (Wang and Enfield, 2001), and the tropical Atlantic SST anomaly area (Rodwell et al., 1999), respectively. According to previous studies (Yin and Ni, 2001; Houghton and Teurre, 1992), there is to some extent a synchronous correlation in SST
changes among the three regions. Obviously such a correlation can be reflected at 1-day scale. Region B corresponds to the southern Indian Ocean, where the correlation of SSTs at 1-day scale is smaller than those in the peripheral regions, i.e., SST in this region may be weakly negatively correlated with some regions elsewhere.

At 15-day scale (Fig. 8b), region A’ corresponds to the Northern Pacific where the temperature correlation is still very small like at 1-day scale, indicating that the negative correlation effect still exists. Region B’ corresponds to the Indian Ocean dipoles (Behera and Yamagata, 2001), with correlation there anomalously higher than peripheral regions, and opposite to that at 1-day scale, indicating that at different time scales, the temperature correlations among regions may qualitatively change. The reason for the correlation anomaly in region B’ might be teleconnections with the other regions instead of SRCs (Reason and Mulenga, 1999). Region C’ (the eastern tropical Pacific) just corresponds to the El Niño area, where the temperature correlation is very small. According to Wang (1995) and Li and Mu (1999), there is a robust negative correlation of SST between the El Niño region and the western tropical Pacific warm pool region, therefore the temperature correlation in region C’ is relatively small. For the memory and homogeneity of temperature changes of oceanic system, relative differences between the three pools and their peripheral regions weakened at 15-day scale, but still can be reflected in Fig. 9. Another difference between 1- and 15-day scales is that at 1-day scale, the area with the minimum correlation lies in mid-latitudes of Northern and Southern Hemisphere, but at 15-day scale, it lies in high latitudes including the two poles. On the whole, the values of CCs over oceans are obviously larger than those over continents, especially at 15-day scale.

Fig. 8. Spatial distributions of average CCs of grid point temperature for (a) 1-day scale and (b) 15-day scale.
Fig. 9. The spatial distribution of average CCs of grid point temperature at 15-day scale in low latitudes (32.5°N–32.5°S).

To analyze the zonal and meridional characteristics of grid point temperature correlation, the zonal and meridional average CCs of grid point temperature at 1- and 15-day scales were calculated. For 1-day scale, the largest value of the zonal average lies at equator. It reduces polewards with the least value at a latitude slightly less than 60° in both the Northern and Southern Hemisphere, and then increases towards the Arctic and the Antarctic, respectively. On the whole, the latitudinal symmetry of CCs is good. For 15-day scale, the distribution of the zonal average of CCs is to some extent similar to that of 1-day scale: the largest value of the zonal average also lies at equator, but its latitudinal symmetry is not so good; the values of the zonal average over 30°–60°N are much smaller than those over 30°–60°S, and the least value lies at a latitude slightly greater than that at 60° in both the Northern and Southern Hemisphere, and then increases slightly towards the Arctic and the Antarctic, respectively (Fig. 10a). The reason for such a distribution may be that for oceanic system, its specific heat is relatively large, and differences of the underlying surface are small. Furthermore, the time scale of 15 day reflects a mean state of grid point temperature changes, therefore differences in temperature changes among neighboring grid points are small and the correlativity of grid point temperature series is good. As for the longitudinal character of CCs (Fig. 10b), the meridional average of CCs at 15-day scale overall shows a longitudinal quasi-symmetric distribution with the largest value at about 10°W and two lower value regions over 20°–100°E and 60°–120°W, respectively. However, the meridional average at 1-day scale is no longer longitudinally symmetric, but in general displays a wavy pattern: it shows out-of-phase variations with that at 15-day scale over 60°E–155°W, and in-phase variations over longitudes elsewhere.
4. Conclusions and discussion

Comparisons of the CCs, the eigenvectors, the eigenvalues and the probability distributions between TCMs and RCM have revealed that there are correlation “noises” as well as real correlations among global grid point temperature series. Real correlations contain SRCs between neighboring grid points, and teleconnections, i.e., LRCs. Under different time scales, SRCs and LRCs behave differently: SRCs dominate temperature correlativity of global grid points at 1–10-day scale, but at 15-day-or-longer scale, the contribution of SRCs declines, while that of LRCs increases. It has been found from eigenvalues and eigenvectors of TCMs and RCM that the major correlation information of global grid point temperature series concentrates in a few eigenvectors with relatively larger eigenvalues, and the projections of grid point temperature series onto these eigenvectors are able to reflect the overall character of global temperature change to a certain extent. Besides, the correlativity of grid point temperature series obviously changes with time and space. The averages of CCs show two different change patterns around 1977, which may correspond to the abrupt change of temperature in the mid-late 1970s. 1948–1977, 1987–1990, and 1999–2002 are three periods of high correlation, when the correlativity of global temperature is better, while 1978–1982 and 1991–1996 are two periods of low correlation, when the regional diversity of global temperature change is distinctive. The CCs at 1- and 15-day scales both show a band-like zonal distribution. The zonal average of CCs at 1-day scale displays a better longitudinal symmetry, while the meridional average at 15-day scale displays a longitudinal quasi-symmetry. Therefore, as far as the correlativity of global temperature is concerned, the grid point temperature series at 1- and 15-day or longer scales may constitute two correlation regimes of different properties (Wang et al., 2005a, b; Gong et al., 2008) with the latter probably more complicated. Using the latest research achievements on complex network to further analyze and interpret such correlation patterns of climatic elements will help us better understand inherent links and rules of climate system, and will possibly provide a new path to the simulation of changes of climatic elements, such as temperature and precipitation. These investigations will be reported in our subsequent papers.

REFERENCES


