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Different spatial cross-correlation patterns of temperature records over China: A DCCA study on different time scales

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HIGHLIGHTS

- Cross-correlations between temperatures of different stations vary with time scales.
- Spatial cross-correlation patterns on different time scales are provided.
- These cross-correlation patterns are useful for the understanding of climate system.
- DCCA is recommended as a reliable method in detecting relations in climatology.

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ABSTRACT

Daily mean temperature records over China during the past 50 years are studied by means of detrended cross-correlation analysis (DCCA). Taking Beijing as a center, we calculate the DCCA cross-correlation coefficient σ_{DCCA} between the temperatures in Beijing and those in other stations. After a statistical significance test, spatial cross-correlation patterns on different time scales are shown in this paper. We find the spatial cross-correlation patterns can vary with time scales. On small time scale of one week to one month, only the temperatures in nearby regions have close relations with that in Beijing, while on larger time scale of intra or inter-seasonal, temperatures in most of the regions, especially in the northeast show high level cross-correlations with that in Beijing. The southwest plateau (including the Tibetan Plateau and the YunGui Plateau) is a special region, where the temperatures take on significant anti-cross-correlations on inter-seasonal scale, but no significant correlations on inter-annual scale. By analyzing these different spatial patterns, we can better understand the influencing climatological processes of different scales. Therefore, DCCA are recommended as a reliable method in detecting the relations between two climatological variables, and further be useful for our understanding of the whole climate system.

1. Introduction

In the past few decades, the cross-covariance and the cross-correlation have been widely used to quantify the similarity of two given time series. They can easily be implemented, and have been used in various fields. Such as in climatology, one usually estimates the cross-correlation between two simultaneously recorded time series, to make climate diagnosis or climate prediction [1–3]. Although the results obtained cannot provide us causality, by analyzing the cross-correlations between two climatic variables, one may still reach useful understandings of the whole climate system.

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However, due to the effects of many external forces such as the solar radiations, volcanic eruptions, as well as the human activities, climatological time series are usually characterized by multi-scale structures. In other words, non-stationarity usually exists [4–7]. Since the traditional cross-correlation analysis is only applicable for stationary time series, and its result cannot provide us the correlation information on different time scales, advanced approaches are therefore required.

During the past five years, a new method based on detrended covariance, detrended cross-correlation analysis (DCCA), has been proposed and widely used in the research of non-stationary time series [8,9]. DCCA is a modification of the standard covariance analysis. By detrending local trends, DCCA ensures that the results obtained are not affected by trend (including linear, quadratic, and even higher order trends and periodic trends) [10,11]. Therefore, this method and its multifractal version [12,13] have been applied to various fields such as economics [9,14,15], seismic studies [16], traffic flows [17,18], as well as geophysical researches [19,11,20]. In fact, DCCA is an expended version of the widely used method, detrended fluctuation analysis (DFA) [21,22], which is a method that performs better than the traditional auto-correlation analysis or the power spectrum density analysis in quantifying the scaling behavior (or long-term auto-correlations) of time series [23,24]. Similar to DFA, but based on covariance, DCCA can provide us information on whether the one time series has long-term cross-correlation with the other simultaneously recorded time series. If the fluctuation function $F_{DCCA}(s)$ obtained from DCCA increases with the time scale s as a power-law, $F_{DCCA}(s) \sim s^{\lambda}$, the two time series are considered to be long-term cross-correlated. In contrast, if $F_{DCCA}(s)$ does not increase as a power-law, or remains zero at different time scales, we believe that the two time series are not long-term cross-correlated [8]. For more details on long-term cross-correlation, one can also refer to Refs. [10,25], especially in Ref. [10], the authors proposed a new test to quantify the presence of cross-correlations.

However, as discussed in Refs. [26,27], the results obtained from DCCA does not quantify the level of cross-correlations. From DCCA, we only know whether the two considered time series are long-term cross-correlated. To quantify the level of cross-correlation, we need to use both the DFA and DCCA methods, in analogy with the cross-correlation coefficient, to calculate the so-called DCCA cross-correlation coefficient σ_{DCCA}, as introduced in Ref. [26].

$$\sigma_{DCCA} \equiv \frac{F^2_{DCCA}}{F_{DFA}(x_i)F_{DFA}(x'_i)}, \tag{1}$$

where $\{x_i\}$ and $\{x'_i\}$ are the two considered time series, and F_{DFA} is the fluctuation function obtained from DFA. It is obvious that σ_{DCCA} is a dimensionless coefficient that ranges from -1 to $+1$. $\sigma_{DCCA} = 0$ means there is no cross-correlation, $\sigma_{DCCA} = 1$ means there is perfect cross-correlation, while $\sigma_{DCCA} = -1$ means there is perfect anti-cross-correlation [26,27].

Considering the advantages of DCCA, such as

(i) DCCA is not affected by trend, and is suitable for the analysis of non-stationary time series;
(ii) DCCA can show us results on different time scales s,

by calculating the DCCA cross-correlation coefficient σ_{DCCA}, we may better understand the cross-correlation behavior between two non-stationary time series. Therefore, this method can be applied to the research of climatology.

In this paper, we mainly focus on the daily mean temperature records over China. We take Beijing, the capital of the country, as a center, and estimated the cross-correlation levels between the temperatures in Beijing and those from other locations. By calculating the DCCA cross-correlation coefficient σ_{DCCA}, we find different spatial cross-correlation patterns on different time scales. For the time scale of one week to one month, only the temperatures in nearby regions have close relations with those in Beijing, while on larger time scale of intra or inter-seasonal, temperatures in most regions, especially in the northeast show high level cross-correlations, but anti-cross-correlations are found on the southwest plateau. On inter-annual time scale, the pattern again becomes different. Although the cross-correlation keeps at a high level in the northeast, in some other regions, such as the southwest plateau and the southernmost of China, significant cross-correlation disappears. These different spatial cross-correlation patterns can be attributed to different processes that affect the temperatures on different scales. Therefore, it will be helpful for our understanding of the whole climatic system.

The rest of this paper is organized as follows. In Section 2, we will make a brief introduction of the data and the method (DCCA) we use for analysis. By calculating the DCCA cross-correlation coefficient between temperatures in Beijing and that from other stations, after applying an uncertainty estimation, results including spatial cross-correlation patterns on different time scales are shown in Section 3. In Section 4, we make a discussion and conclude this paper.

2. Data and methodology

2.1. Data

In this paper, daily mean temperature records from 461 stations over China are used for our analysis. The data are obtained from the China Meteorological Data Sharing Service System (http://cdc.cma.gov.cn), with length of 50 years, from 1962 to 2011. All the records have been quality controlled, with missing values no more than 100 days. The geographical distribution of the 461 stations are shown in Fig. 1.

Before our analysis, we first calculate the temperature anomalies by eliminating the periodic annual cycle as $\tau_i = T_i - \langle T_i \rangle$ [23], where T_i is the daily mean temperature records, $\langle T_i \rangle$ is the annual cycle averaged from each calender date, and τ_i is the temperature anomalies which we use for the analysis. From Fig. 2, we can see that the periodic components within one year are removed successfully.

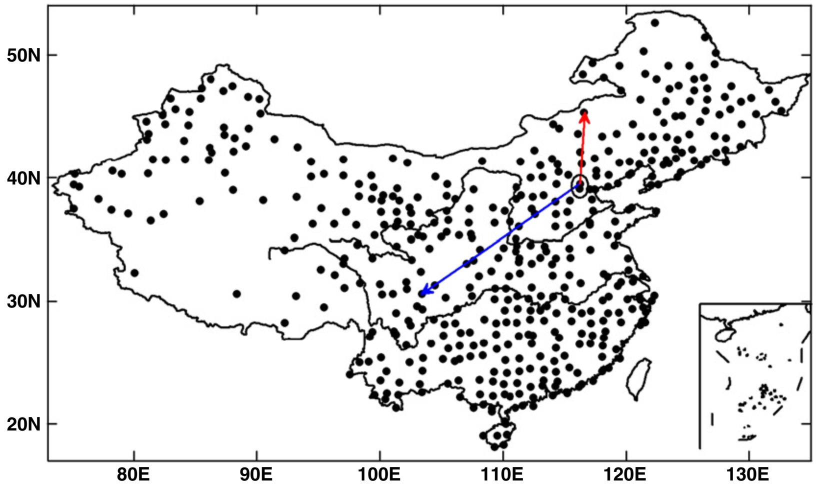

Fig. 1. Geographical distribution of the 461 stations used in this study. The black circle in the northeast marks two stations: Beijing (39.8N, 116.5E) and Langfang (39.1N, 116.4E), while the two arrows point to the other two stations: Dongwuqi (45.5N, 117.0E) and Dujiangyan (31.0N, 103.7E).

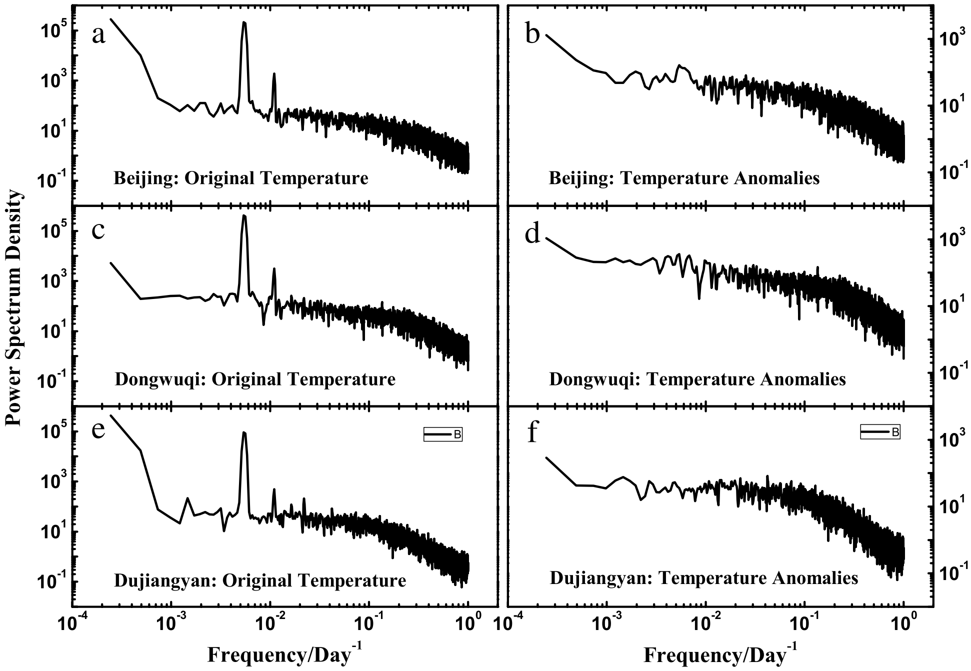

Fig. 2. Power spectrum density of temperatures in three randomly selected stations: Beijing (a, b), Dongwuqi (c, d), and Dujiangyan (e, f). Figures in LHS (a, c, e) are results of original temperature records $\{T_i\}$, while figures in RHS (b, d, f) are results of temperature anomalies $\{\tau_i\}$. One can see that the periodic components within one year are removed successfully in $\{\tau_i\}$.

2.2. Methodology

2.2.1. Brief introduction of DCCA

Before we show the detrended cross-correlation analysis (DCCA), we would like to make a brief introduction of the detrended fluctuation analysis (DFA) first [22]. In DFA, one considers the cumulated sum (profile) $Y_k = \sum_{i=1}^{k} x_i$ of *one* record of interest $\{x_i\}$, where $i = 1, 2, 3, \ldots, N$. By dividing the profile into Ns non-overlapping windows of size s (where $Ns = [N/s]$), in each window ν, we can determine the "detrended walk" as the difference between the original walk $Y_{k,\nu}$ and the local trend $\widetilde{Y_{k,\nu}}$, and further calculate the variance as:

$$f^2_{DFA}(s, \nu) \equiv \frac{1}{s} \sum_{k=(\nu-1)s+1}^{\nu s} (Y_{k,\nu} - \widetilde{Y_{k,\nu}})^2. \tag{2}$$

The detrended fluctuation function is thus defined as

$$F_{DFA}(s) \equiv \sqrt{\frac{1}{Ns}\sum_{\nu=1}^{Ns} f_{DFA}^2(s,\nu)}, \tag{3}$$

where Ns is the number of the windows, and $\nu = 1, 2, 3, \ldots, Ns$. If $F_{DFA}(s)$ increases by a power law, $F_{DFA}(s) \sim s^{\alpha}$, with the exponent $\alpha > 0.5$, we say the record $\{x_i\}$ is long-term auto-correlated [22].

Analogously, when considering two time series $\{x_i\}$ and $\{x'_i\}$, we in DCCA again calculated the cumulated sum (profile) $Y_k = \sum_{i=1}^{k} x_i$ and $Y'_k = \sum_{i=1}^{k} x'_i$ first, and then divide the entire time series into Ns windows of size s. Since DCCA is based on covariance, we in each window calculate the covariance of the "detrended walk":

$$f_{DCCA}^2(s,\nu) \equiv \frac{1}{s}\sum_{k=(\nu-1)s+1}^{\nu s} (Y_{k,\nu} - \widetilde{Y_{k,\nu}})(Y'_{k,\nu} - \widetilde{Y'_{k,\nu}}). \tag{4}$$

The detrended covariance is thus defined as

$$F_{DCCA}(s) \equiv \sqrt{\frac{1}{Ns}\sum_{\nu=1}^{Ns} f_{DCCA}^2(s,\nu)}. \tag{5}$$

If $F_{DCCA}(s)$ increases with s by a power law, $F_{DCCA}(s) \sim s^{\lambda}$, the two considered time series are believed to be long-term cross-correlated. Whereas, if $F_{DCCA}(s)$ does not increase by a power law, or remains zero at different time scales s, the two time series are not long-term cross-correlated [8].

It is worth to note that the reason why the method DCCA (or DFA) is not affected by the trend, is that the covariance (or variance) is calculated from "detrended walk". Therefore, the fitting of the local trend $\widetilde{Y_{k,\nu}}$ is important in the method. We can select an appropriate order of the polynomial fitting to remove the effect of local trend. As discussed in Ref. [11], the authors proposed a varying order of the polynomial fitting, to remove the effect of periodic trends. However, as shown in Fig. 2, the temperature anomalies $\{\tau_i\}$ we study do not suffer much from the periodic trends, and former works [28,29] have shown that only cubic polynomial fitting of the local trend $\widetilde{Y_{k,\nu}}$ is enough for the accurate estimation of long-term correlations in temperature anomaly time series. Therefore, in this study we choose to use the cubic polynomial fitting, and the method can be denoted as DCCA-3.

To assess the cross-correlation level, as introduced above, [26] proposed the so-called DCCA cross-correlation coefficient σ_{DCCA}, which is defined as the ratio between $F_{DCCA}^2(s)$ and the product of the two detrended variance functions $F_{DFA}(s)$, and $F'_{DFA}(s)$, as shown in Eq. (1). σ_{DCCA} ranges from -1 to $+1$. For $\sigma_{DCCA} > 0$, the larger the σ_{DCCA} is, the higher the cross-correlation level will be; for $\sigma_{DCCA} < 0$, the smaller the σ_{DCCA} is, the higher the anti-cross-correlation level will be.

2.2.2. Usability of DCCA

To better illustrate the usability of DCCA in dealing with the non-stationary time series, in this section, we will make a comparison between DCCA and the traditional cross-correlation analysis. Fig. 3(a)–(c) shows temperature anomalies from three stations: Beijing (39.8N, 116.5E), Huma (51.7N, 126.7E), and Pishan (37.6N, 78.3E). One can see by eye that the temperature anomalies are all taking on increasing trend, which means that the time series are non-stationary. If we make a cross-correlation analysis between them directly, the cross-correlation coefficients can be overestimated, as shown in Fig. 3(f). Similar results can also be obtained in artificial data. In Fig. 3(d) and (e), we show two independent white noises, which means the cross-correlation between them should be zero. However, if we add an external trend to both time series, the cross-correlation is again overestimated, as shown in Fig. 3(f).

Of course, for the examples in Fig. 3, we can first fit and remove the trend before the analysis. In this way, the cross-correlation coefficients obtained can be accurate, as shown in Fig. 3(f). However, for most climatological time series, one cannot tell in advance the trend, especially the local trend hidden in the time series. Therefore, to deal with the non-stationary time series, we need to use DCCA.

Fig. 4 shows the results of DCCA-3. We use three pairs of artificial time series (not shown here) for illustration. Pair I are two long-term correlated time series generated from the same white noise (For the method of how to generate long-term correlated time series from white noise, please refer to Ref. [30].) Their DFA results and DCCA results are shown in Fig. 4(a). Pair II are two long-term correlated time series generated from different white noises. Their results are shown in Fig. 4(b). Pair III are two time series obtained by adding external trend (quadratic trend) to the time series of Pair I. Their results are shown in Fig. 4(c). One can see clearly that, the results of Pair I and Pair III are exactly the same, which means DCCA-3 is not affected by the quadratic trend. By calculating the cross-correlation coefficients, we can find $\sigma_{DCCA} = 1$ at all time scales (see Fig. 4(d)), which is as expected since the time series of Pair I (or Pair III) are generated from the same white noise. On the contrary, for the time series of Pair II which is generated from different white noises, the DCCA fluctuation function $F_{DCCA}(s)$ remains zero at all time scales (see Fig. 4(b), open circles), and the cross-correlation coefficients σ_{DCCA} are also zero (see Fig. 4(d)). This indicates that the two time series of Pair II are not cross-correlated at any time scales.

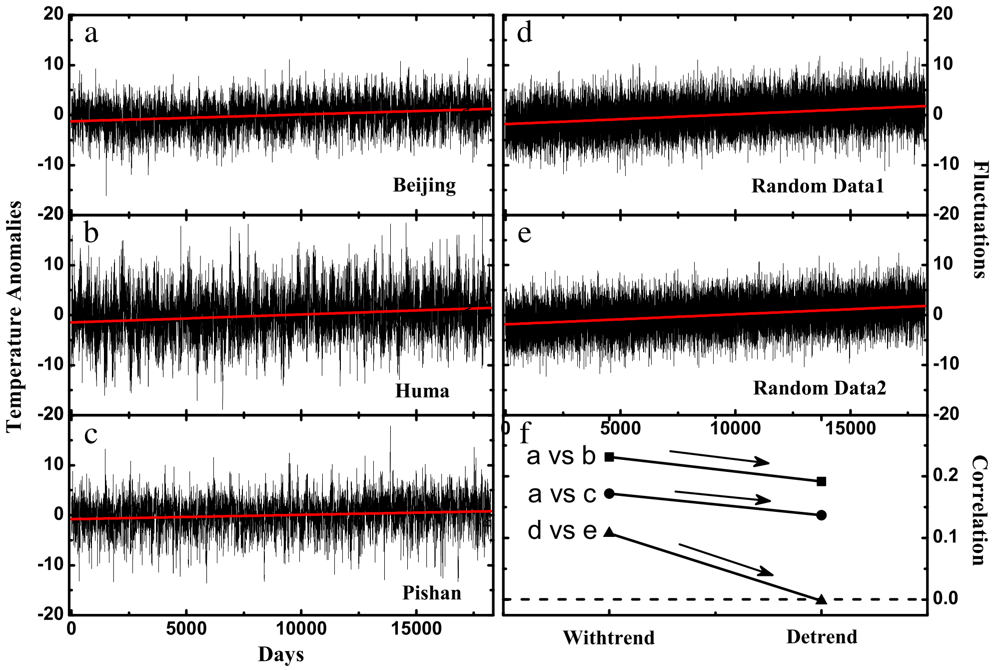

Fig. 3. (a–c) shows temperature anomalies of three stations: Beijing (39.8N, 116.5E), Huma (51.7N, 126.7E), and Pishan (37.6N, 78.3E). (d–e) shows two randomly generated time series with linear trends. (f) shows the cross-correlation coefficients between series in (a) and (b), series in (a) and (c), and series in (d) and (e). One can see that the cross-correlation coefficients are overestimated due to the existence of an external trend.

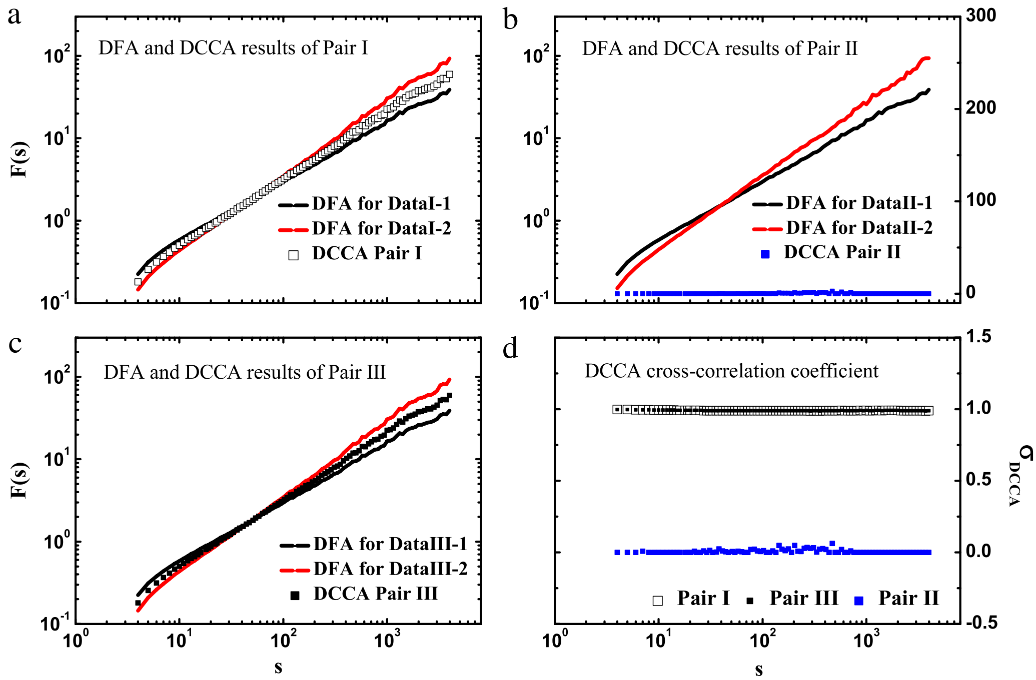

Fig. 4. DCCA results of three pairs of artificial time series. Pair I are two long-term correlated time series generated from the same white noise; Pair II are two long-term correlated time series generated from different white noise; while Pair III are the two time series in Pair I with external trends added. The DFA and DCCA results are shown in (a–c), where the black and red (thick) curves represent the DFA results, while the DCCA results are shown as scattered points. Note that the DCCA results in (b) should refer to the coordinate axis on the right side. The DCCA cross-correlation coefficients σ_{DCCA} are shown in (d).

From the above discussion, we believe that DCCA is a reliable method that can be used to detect the cross-correlations of two non-stationary time series. In the following, we will apply this method to the daily mean temperature records over China.

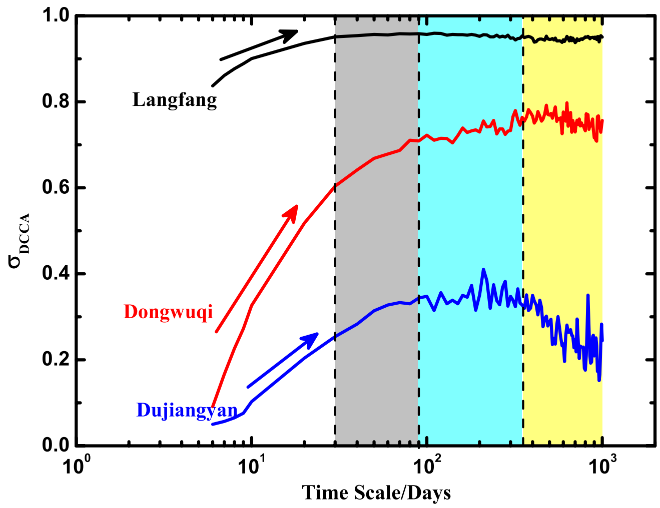

Fig. 5. DCCA cross-correlation coefficient σ_{DCCA} between the temperatures in Beijing and that in three representative stations: Langfang (black), Dongwuqi (red), and Dujiangyan (blue). One can see that the coefficient varies with time scales.

3. Results

We take Beijing (39.8N, 116.5E), the capital of China, as the center. By calculating the DCCA cross-correlation coefficients σ_{DCCA} between the temperatures in Beijing and that in other stations, we can describe the spatial relations at different time scales s.

We first take the results of three representative stations for illustration. See Fig. 1, the three stations are: Langfang (39.1N, 116.4E), Dongwuqi (45.5N, 117.0E), and Dujiangyan (31.0N, 103.7E). Their geographical positions are shown in Fig. 1, and the spatial cross-correlations with Beijing are shown as black, red, and blue curves in Fig. 5. One can see that at small time scales ($6 < s < 30$ days), the cross-correlation levels are relatively lower. With the increasing of the time scale, all the three σ_{DCCA} values increase remarkably. At the intra-seasonal scale ($30 < s < 90$ days), the cross-correlation level between Langfang and Beijing has reached a plateau phase (black curve), while the σ_{DCCA} of the other two cases are still rising. At the inter-seasonal scale ($90 < s < 360$ days), the cross-correlation level between Dujiangyan and Beijing arrives at a plateau phase (blue curve), while the upward trend of σ_{DCCA} between Dongwuqi and Beijing is still not over (red curve). When the scale is larger than one year, the σ_{DCCA} between Dujiangyan and Beijing begins to decrease with the increasing of s, while the σ_{DCCA} of the other two cases do not change much.

From Fig. 5, we confirm that the temperatures from two stations can have different cross-correlation levels on different time scales. This variation can be attributed to different processes that affect the temperatures on different scales. Therefore, studying the cross-correlation levels on different time scales is valuable for our understanding of the whole climate system. Besides the variation of σ_{DCCA} with different time scales, we would like to note that the variation of σ_{DCCA} with different "Couples", or the spatial cross-correlation pattern, is also very important. Such as in Fig. 5, due to the close distance between Langfang and Beijing (only about 74 km), the temperature records in Langfang have a high cross-correlation level with that in Beijing ($\sigma_{DCCA} > 0.9$ when $s > 30$ days). While for the other two stations, the cross-correlation levels are much lower. Therefore, according to the above discussion, two aspects will be considered in this study. One is the spatial pattern of σ_{DCCA} on a given time scale, the other is the variation of σ_{DCCA} with different time scales.

In the following, we will calculate the DCCA cross-correlation coefficients σ_{DCCA} between the temperatures in Beijing and that in all the other 460 stations. Before we show the results, however, we need to make a statistical test to determine a criterion, with which we can tell whether the DCCA cross-correlation coefficients σ_{DCCA} between two given time series are significant, or not [31]. Since all the temperature records over China are long-term correlated, and the mean DFA exponent $\alpha \approx 0.65$, we in this study generated 1000 artificial long-term correlated time series with $\alpha = 0.65$. Because the artificial time series are generated from different white noises, there should be no cross-correlations between them. Therefore, we calculate the DCCA cross-correlation coefficients σ_{DCCA} between the artificial data and the temperatures in Beijing, to determine the criterion, or error bar of the mean coefficients $\overline{\sigma_{DCCA}}$ at each time scale. As shown in Fig. 6, $\overline{\sigma_{DCCA}}$ averaged from all the 1000 samples keeps zero at all the time scales, which is as expected. But the error bar varies. The larger s is, the bigger the error bar we will get. In this study, the error bars we calculate represent the confidence interval of 95%. One can see from Fig. 6 that, when s reaches 2000 days, the uncertainty range σ_Q can be $[-0.3, 0.3]$, where $Q = 0.95$ is the confidence probability. Therefore, if the DCCA cross-correlation coefficient σ_{DCCA} falls out of the uncertainty range σ_Q, we believe the cross-correlation is significant (under the confidence probability of Q). While if σ_{DCCA} falls in the uncertainty range σ_Q, the cross-correlation should be considered as insignificant.

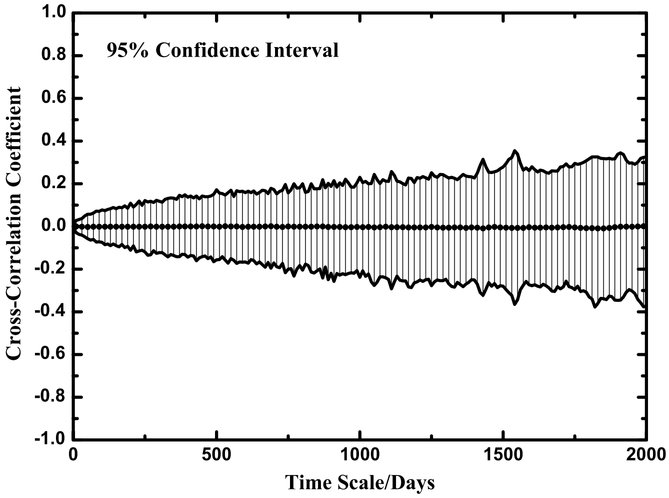

Fig. 6. Uncertainty test of the cross-correlation coefficient σ_{DCCA} on different time scales. The uncertainty range (confidence interval) is determined by counting the DCCA cross-correlation coefficients σ_{DCCA} between the temperatures in Beijing and 1000 artificial time series. When the σ_{DCCA} obtained falls out of the uncertainty range, one believe that the cross-correlation is significant. The uncertainty range is estimated with the confidence probability of 0.95.

Taking the uncertainty range σ_Q into account, we in Fig. 7 show the spatial cross-correlation patterns of different time scales. Areas with red color represent regions with significant cross-correlation, while blue color stands for significant anti-cross-correlation. Areas without color are thus the regions where the cross-correlations are not significant. Fig. 7(a) and (b) are the patterns when the time scale is smaller than one month, where $6 < s < 10$ days for Fig. 7(a), and $6 < s < 30$ days for Fig. 7(b); Fig. 7(c) and (d) are the patterns when the time scale is larger than one month, but smaller than one year, where $30 < s < 90$ days for Fig. 7(c), and $90 < s < 360$ days for Fig. 7(d); Fig. 7(e) and (f) are the patterns when the time scale is larger than one year, where $360 < s < 720$ days for Fig. 7(e), and $720 < s < 1000$ days for Fig. 7(f). The thick black line in each figure is the isoline of $\sigma_{DCCA} = 0.5$.

On the time scale of about one week, we can find that only the temperatures in nearby regions have high cross-correlations with that in Beijing, as shown in Fig. 7(a). No significant cross-correlations can be found in the south and the west of China, due to the long-distant. This result is understandable, and can be attributed to different synoptic scale disturbances. On the time scale of one week to one month, the cross-correlation pattern does not change much, as shown in Fig. 7(b), only with a wider region where significant high cross-correlation exists.

However, when the time scale increases to intra-seasonal, or even inter-seasonal, different patterns arise. See Fig. 7(c) and (d), we can find that the temperatures in most regions over China, except the southwest (including the Tibetan Plateau), show significant (positive) cross-correlations with the temperatures in Beijing. Especially in the northeast, the cross-correlations have reached a high level (refer to the isoline of $\sigma_{DCCA} = 0.5$), which indicates that the temperatures in these regions may have similar varying mode with that in Beijing at the intra and inter-seasonal scales. That is, when Beijing has a colder winter, for example, the regions with red color may also experience a colder winter. This result is also understandable. In the intra-seasonal or inter-seasonal time scale, synoptic disturbances have been filtered, and processes with longer life cycle begin to play a more important role. Since this kind of processes usually can sustain for a long time with enough energy, the affected area is often large. Such as the Arctic Oscillation (AO), it is believed that when the AO index is negative, there tends to be high pressure in the polar region, weak zonal winds, and greater movement of frigid polar air into middle latitudes [32–34]. In this situation, the north and the northeast of China may experience a colder winter, which in our study, corresponds to the significant cross-correlations at inter-seasonal time scale. It is worth to note that the results in the southwest of China, including the Tibetan Plateau and the YunGui Plateau, are totally different from that in other regions (see Fig. 7(c) and (d)). The temperatures on the plateau have significant anti-cross-correlations with the temperatures in Beijing (the blue area), while temperatures in the junction between the plateau and the nearby lower-lying regions do not show significant cross-correlations (the white area), behaving like a transition zone. This pattern indicates that, "protected" by the high altitude, temperatures on the Tibetan Plateau and the YunGui Plateau have different (maybe opposite) varying modes from that in lower-lying regions.

On the time scale of larger than one year, as shown in Fig. 7(e) and (f), the anti-cross-correlations between the temperatures on the plateau and that in Beijing disappear. Meanwhile, temperatures in the southeast of China also show much weaker cross-correlations. Only in the north, especially the northeast, the cross-correlation pattern maintains in a high level. Obviously, the absence of cross-correlation in the southwest of China can be due to the special climatic conditions on the plateau, while the weaker cross-correlations in the southeast may be attributed to the impacts of many multi-scale processes, such as the ENSO [35], as well as the influence from the Tibetan Plateau [36,37], etc. In fact, it is not surprising that the annual temperatures in the south vary differently from that in the north of China. As discussed in Ref. [38], there are

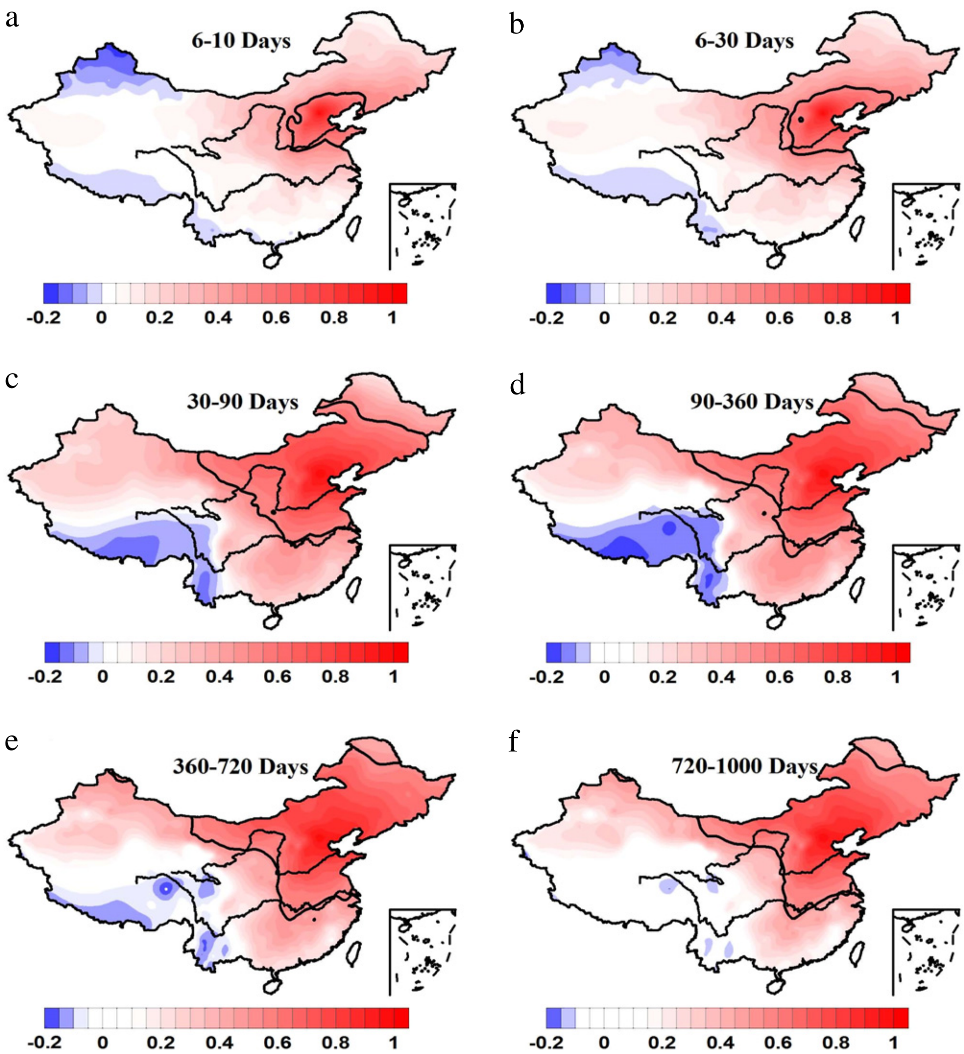

Fig. 7. Spatial cross-correlation patterns on different time scales. Red color represents significant cross-correlation, blue color represents significant anti-cross-correlation, while areas without color are the regions where the cross-correlations are not significant. The thick black line in each figure is the isoline of $\sigma_{DCCA} = 0.5$. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

two temperature modes in the East Asia (EA): the northern mode and the southern mode, and these modes are primarily associated with inter-annual variations.

4. Discussion and conclusion

In this paper, we studied the daily mean temperature records over China by means of the detrended cross-correlation analysis (DCCA). By calculating the DCCA cross-correlation coefficients σ_{DCCA} between the temperatures in Beijing and that in other stations, we provide the spatial cross-correlation pattern on different time scales. We find in the time scale of one week to one month ($6 < s < 30$ days), only the temperatures in nearby regions have close relations with that in Beijing, and the cross-correlation level σ_{DCCA} decreases very fast with the distance. This pattern can be attributed to the fast changing synoptic scale disturbances. However, when the time scale increases to intra or inter-seasonal ($30 < s < 360$ days), influenced by processes with longer (intra-annual) life scale, a different spatial pattern arises. In this scale, temperatures in most regions, especially in the northeast, take on high level cross-correlations. While temperatures in the Tibetan Plateau and the YunGui Plateau show significant anti-cross-correlations. In fact, even though the anti-cross-correlations are significant, their levels are low with $\sigma_{DCCA} \approx -0.15$. When the time scale is larger than one year ($s > 360$ days), the anti-correlations between the temperatures on the southwest plateau and that in Beijing disappear. Besides the southwest plateau, cross-correlation levels in the southeast also become much lower in inter-annual scale, but in the northeast, the cross-correlations still keep in a high level.

Our reasons for using DCCA in this paper are mainly based on two points: (i) DCCA is suitable for the analysis of non-stationary time series; (ii) DCCA can provide us results on different time scales. Actually, our study is only a simple application of DCCA to the climatological research. Through this research, we believe that DCCA can be a reliable method in detecting the relations between two climatological variables. By applying DCCA, many issues can be studied in a more detailed way. For example, we can analyze the cross-correlations of two time series on different time scales, and further find the corresponding factors that control the correlation pattern. By calculating the DCCA cross-correlation coefficient σ_{DCCA} between time series of different locations, we may further construct a climate network, which can be useful for the climate diagnosis or prediction. Therefore, many works are needed in the future, and we will report the relevant results in the following papers.

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