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Different scaling behaviors in daily temperature records over China

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ABSTRACT

Long-range correlations of five kinds of daily temperature records (i.e. daily average temperature records, daily maximum temperature records, daily minimum temperature records, diurnal temperature range and the sum of daily maximum and minimum temperature records) from 164 weather stations over China during 1951–2004 are analyzed by means of detrended fluctuation analysis (DFA). These five kinds of fluctuation series are found to be power-law correlated with scaling exponents larger than 0.5. Local changes of scaling exponents are examined and the spatial distributions of these different kinds of temperature records are similar except the diurnal temperature range (DTR for short) records. Furthermore, the differences of the scaling behavior among diurnal temperature records and other kinds of temperature records are discussed.

1. Introduction

As a well known phenomenon, a warm day is more likely to be followed by a warm day and vice versa [1]. On a longer scale of about a week, a warmer week is usually followed by a colder week, since the general weather system usually lasts for about seven days [2,3]. This phenomenon can be described as short-term correlations. However, for longer timescales, there still can be correlations between two moments with larger time interval, which can be called long-term correlation. Long-term correlation has become very popular during the last few decades. It has been studied in many fields, such as DNA [4,5], heart rate dynamics [6,7], economical time series [8–10], extreme value analysis [11,12], and so on. Here we mainly focus on weather records. Long-term correlation for weather processes is very important, but hard to define, since the processes of longer timescales are often governed by different processes in nature, such as circulation patterns and trends induced by global warming [13,3]. To solve this problem, it is necessary to remove the non-stationary effects from a time series. Therefore a method, detrended fluctuation analysis (DFA), first developed by C-K Peng has been widely used [4]. DFA is essential to distinguish trends from long-range fluctuations which are intrinsic to the data, which makes this method reliable for the detection of long-range correlations.

Recently, DFA has been applied to different kinds of meteorological variables such as temperature [14,1,15–17,3], wind speed [18,19], relative humidity [20], and cloud breaking [21], etc. Here we focus on the results concerning temperature. The long-term persistence of temperature can be characterized by an autocorrelation function, $C(n) \sim n^{-\gamma}$, which decays as a power law. In the autocorrelation function, the observations are separated by a time lag n, and γ can be used to characterize the long-term correlation of a time series. In the last decade, there have been many studies on the long-term correlation of temperature records. Some researchers proposed that the asymptotic power-law correlations for temperature time series may be universal [14,15]. However, in the following years, more and more studies showed that the exponents can be different. Some works showed the exponent γ is roughly equal to 0.7 for continents and 0.4 for oceans [16,22,23].

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Some works argued that the exponents can have a wide range and are dependent on geographic location [24,13,25–27]. Furthermore, some studies found that there are different correlation exponents between daily minimum and maximum temperature records even for the same weather station [25]. Thus two questions arise: What are the scaling exponents of temperature time series obtained from DFA distributed over China, universal or not? For different kinds of temperature records, such as maximum records, minimum records, and diurnal temperature range (the daily maximum records minus the daily minimum records, DTR for short), will there exist any differences among the scaling exponents, and if so, what are the differences?

To answer the questions above, we study the fluctuations of temperature records at 164 weather stations over China. Five kinds of daily temperature time series (daily average temperature records, daily maximum temperature records, daily minimum temperature records, DTR and the sum of daily maximum and minimum temperature records (Sum for short)) are analyzed using DFA. (It should be noted that the daily average temperature records are derived from calculating the average of four observations at different times, so the statistical properties are different from that of the Sum records.) Then the spatial distributions of scaling exponents are shown and differences of the results among these five kinds of time series are discussed. The rest of this article is organized as follows. In Section 2, we will give a short introduction to the data sets we used and the analysis method, DFA. Long-range correlation analysis for these five kinds of time series over China, and their geographical distributions, are presented in Section 3. In Section 4, the differences of these five kinds of time series are discussed. Finally, we conclude this paper in Section 5.

2. Methodology and data

2.1. Methodology outline

Consider a temperature fluctuating time series T_i ($i = 1, 2, 3, \ldots, N$) at a certain meteorological station. The index i counts the days in the record, so the series is sampled at equidistant times $i\triangle t$. In order to remove the seasonal trends, we first calculate the departures of T_i from the mean temperature $\langle T_i \rangle_d$ for each calendar date i, $T_i = T_i - \langle T_i \rangle_d$, and get a new time series, $\triangle T_i = T_i - \langle T_i \rangle_d$. Obviously the mean value of the new series is zero and the persistence can be characterized by the auto-correlation function

$$C(s) = \langle \triangle T_i \triangle T_{i+s} \rangle = \frac{1}{N-s} \sum_{i=1}^{N-s} \triangle T_i \triangle T_{i+s}, \tag{1}$$

where N is the length of the record and s is the time lag. However, it is difficult to calculate $C(s)$ directly because of the existence of noise and underlying trends of unknown origin in the finite temperature series. Thus, we calculate the temperature profile of the time series first as

$$Y_k = \sum_{i=1}^{k} \triangle T_i. \tag{2}$$

After that, the profile series is divided into non-overlapping segments of equal length s indexed by $k = 1, 2, 3, \ldots, N_s$ with $N_s = [N/s]$. Since the length of the series is not always a multiple of s, as a result, there will often remain a short part left at the end of the profile. To solve this problem, the same procedure is repeated from the other end of the record [28], and we get $2N_s$ segments altogether. Next, in each segment, the local trend is calculated by a polynomial fit. For a given segment length s, we can get the corresponding square fluctuation of the kth segment $F_s^2(k)$ as the variance of the profile subtracted from the polynomial fit in the kth segment. Then the root-mean-square fluctuations $F(s)$ is obtained by averaging over all segments of size s,

$$F(s) = \sqrt{\frac{1}{2N_s} \sum_{k-1}^{2N_s} F_s^2(k)}. \tag{3}$$

For different segment length s, $F(s)$ will be different. For the case of long-range power law correlations, it will increase as a power law

$$F(s) \sim s^{\alpha}, \tag{4}$$

with $0 < \alpha < 1$. Notice the power-law auto-correlation function

$$C(n) \sim n^{-\gamma}, \tag{5}$$

the exponent α and γ are connected as [14,28,25,2]

$$\gamma = 2(1 - \alpha). \tag{6}$$

Consequently, for uncorrelated data, we have $\alpha = \frac{1}{2}$, long-memory (persistent) processes are characterized by $\alpha > \frac{1}{2}$, and anti-persistent signals exhibiting negative long range correlations by $\alpha < \frac{1}{2}$ [4,29].

It is worth noting that there are different orders of DFA, such as DFA1, DFA2, etc. The order corresponds to the order of the polynomial used in the fitting procedure. According to this definition, DFAn can eliminate trends of order n in the profile