GEOPHYSICAL RESEARCH LETTERS, VOL. 34, L07804, doi:10.1029/2006GL027755, 2007

Long-range correlations in daily relative humidity fluctuations: A new index to characterize the climate regions over China

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Received 3 August 2006; revised 5 December 2006; accepted 15 February 2007; published 7 April 2007.

[1] Daily relative humidity anomaly records of 73 stations over China have been analyzed by the method of Detrended Fluctuation Analysis (DFA for short). It is obvious that the relative humidity fluctuations take different statistical behavior from other meteorological quantities and it is found their average scaling exponent is higher than that of the temperature fluctuations. When the scaling exponents obtained from the DFA is plotted versus the standard deviation of the relative humidity fluctuations, no obvious correlation or patch behavior can be found over different areas and climate regions. So the product of the scaling exponent and the standard deviation of the same record is proposed to form a new climate region classifying index.
Citation: Chen, X., G. Lin, and Z. Fu (2007), Long-range correlations in daily relative humidity fluctuations: A new index to characterize the climate regions over China, *Geophys. Res. Lett.*, *34*, L07804, doi:10.1029/2006GL027755.

1. Introduction

[2] Climate changes receive wide attention from governments and the public throughout the world. So are there any trends among climate changes or long-range correlations within the climate system? The answer seems to be positive since a global warming background in the last few decades has been reported by the IPCC [*Dai et al.*, 1998; *Zhai and Pan*, 2003; *Zhai et al.*, 2005; *Zou et al.*, 2005]. Then it becomes more important how to exactly address the impact from these trends on the long-range correlations. Fortunately, a method called Detrended Fluctuation Analysis (DFA for short) invented by *Peng et al.* [1994, 1995] has proven useful in the detection of long-range correlations in a time series with non-stationarities induced by some trends in the fluctuations of different quantities. It has been applied successfully to diverse fields such as human gait [*Hausdorff et al.*, 1995], DNA sequences [*Peng et al.*, 1994, 1995], heart rate dynamics [*Bunde et al.*, 2000], neural receptors in biological systems [*Bahar et al.*, 2001], economical time series [*Ausloos and Ivanova*, 2000; *Liu et al.*, 1997], and long-time weather records [*Király and Jánosi*, 2005; *Koscielny-Bunde et al.*, 1996, 1998; *Kurnaz*, 2004]. Many previous works have applied the method of DFA as well as R/S analysis and Wavelet Transformation to analyze the temperature fluctuations over a period of decades on different parts of the globe and revealed a power-law correlation which can be characterized by an autocorrelation function $C(n) \sim n^{-\gamma}$, where n is the time between the observations. However, there are some disagreements on the scaling exponent γ. Different groups have shown that this exponent γ has roughly the same value $\gamma \approx 0.7$ for continental stations [*Bodri*, 1994, 1995; *Bunde and Havlin*, 2002; *Eichner et al.*, 2003; *Kantelhardt et al.*, 2001; *Koscielny-Bunde et al.*, 1996; *Talkner and Weber*, 2000; *Weber and Talkner*, 2001], and roughly 0.4 for island stations [*Bunde and Havlin*, 2002; *Eichner et al.*, 2003]. On the other side, some groups claimed that the scaling exponent will increase when the distance from the sea increases, and that the scaling exponent γ is roughly close to 0 over the oceans, roughly 1 over the inner continents and roughly 0.7 in transitional regions [*Blender and Fraedrich*, 2003; *Fraedrich and Blender*, 2003, 2004]. Thus, it seems considerable work remains to be done concerning this issue.

[3] China is a large country with a significant portion of land territory of the world, it has different geophysical distributions and several specific climate regions. Thus, the climate changes over China may vary from place to place. To reveal the climate changes over specific regions, we need to carefully characterize the trends among climate changes or long-range correlations within the climate system. In this paper, we attempt to study long-range correlations in relative humidity based on the daily relative humidity data set of 194 stations in mainland China during the second half of the 20th century. We attempt to applied DFA to the daily relative humidity anomaly records of 73 stations in China. A similar power-law correlation which also can be characterized by the function $F(n) \sim n^{\alpha}$ has been observed. When plotting the scaling exponents obtained from the DFA versus the standard deviation of the relative humidity fluctuations, the dots which represented different areas and climate can not always be separated clearly. Thus, we introduce a new index χ, by which the arid or semi-arid and humid areas can be determined clearly.

2. Methodology and Data

2.1. Methodology Outline

[4] First, let us briefly recall some steps of DFA (details of DFA can be found in Peng's papers and explanation in his Web site (http://reylab.bidmc.harvard.edu/download/DFA/intro/)), the time series to be analyzed (with N samples) is first integrated. Next, the integrated time series is divided into boxes of equal length, n. In each box of length n, a least squares line is fit to the data (representing the trend in that box). The y coordinate of the straight line segments is denoted by $y_n(k)$. Next, we detrend the integrated time series, $y(k)$, by subtracting the local trend, $y_n(k)$(The results shown in this paper is from only linear fit of detrending

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0094-8276/07/2006GL027755$05.00

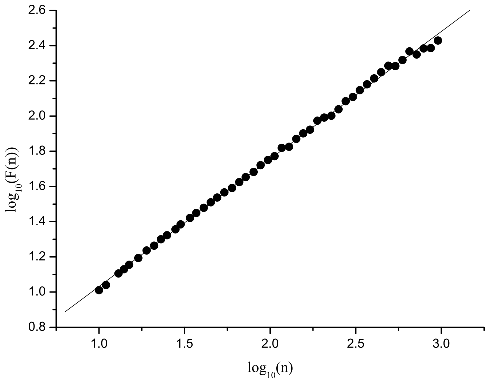

Figure 1. The log-log plot of $F(n)$ vs n for a specific station(50353 Huma).

polynomials in the DFA procedure, but two order and three order of detrending polynomials are also used in DFA procedure, similar results can be obtained), in each box. The root-mean-square fluctuation of this integrated and detrended time series is calculated by $F(n) = \sqrt{\frac{1}{N}\sum_{k=1}^{N}[y(k) - y_n(k)]^2}$. This computation is repeated over all time scales (box sizes) to characterize the relationship between $F(n)$, the average fluctuation, as a function of box size. Typically, $F(n)$ will increase with box size n. A linear relationship on a log-log plot indicates the presence of power law (fractal) scaling. Under such conditions, the fluctuations can be characterized by a scaling exponent α ($\gamma = 2(1 - \alpha)$ [*Koscielny-Bunde et al.*, 1998; *Talkner and Weber*, 2000]), the slope of the line relating log $F(n)$ to log n. Consequently, persistent processes are characterized by the exponent $\alpha > 0.5$, uncorrelated time series (e.g., pure random walk) obey $\alpha = 0.5$, anti-persistent signals have $\alpha < 0.5$ characterization.

2.2. Data Sets

[5] The records used in this paper were obtained from a high-quality daily surface climatic data sets, processed by Chinese National Meteorological Information Center (NMIC), of 194 Chinese meteorological stations taking part in international exchange. The same collection was utilized in many studies to analyze climate change over China in the recent 50 years [*Qian and Lin*, 2005; *Zhai and Pan*, 2003; *Zhai et al.*, 2005; *Zou et al.*, 2005]. The main data sets used in this paper are relative humidity time series, which is defined as $e = \frac{p_v}{p_{sat}(T)}100\%$, where the partial vapor pressure p_v of gaseous water in air is used to quantify the air humidity [*Vattay and Harnos*, 1994]. At a given temperature T, the amount of water in air is limited. The maximum partial vapor pressure corresponding to the maximum water content is the saturation vapor pressure $p_{sat}(T)$. There are totally 194 records, among which three ones are too short (only 10 years long) to give a reliable results as others (with length about 50 years from 1951 to 2000), so they are excluded. Among the left 191 records, only 73 records are without missing values and/or bad measured values and they can nicely cover most of areas of China except Tibetan region, so these 73 records are chosen to analyze the climate region classification. Other 118 records are with missing values and/or bad measured values, although these numbers of points are much less (less than 5%) compared to the whole record, in order to give a reliable result, we also omit these 118 records. Actually, even we include these 118 records, all conclusions given in this letter will change little (results are not shown in this letter).

[6] Daily relative humidity data have a non-stationary nature due to seasonal trends, we can eliminate them by subtracting the annual cycle from our raw data e_i (daily mean R-H) by computing the anomaly series $e_i' = e_i - \langle e_i \rangle_d$, where $\langle\rangle_d$ denotes the long-time average value for the given calendar day.

3. Long-Range Correlation Analysis for Relative Humidity and Geographical Distribution

[7] First of all, let us check the long-range correlations in the relative humidity time series. Figure 1 shows the log-log plot of $F(n)$ vs n for a specific station, it is clear that there is a prominent linear relation between $\log_{10}F(n)$ and $\log_{10}n$ over rather broad ranges with a same scaling exponent $\alpha = 0.72$, indicating that there is long-range correlation in the relative humidity fluctuations. Actually, for all 73 stations there exist similar long-range correlations in the relative humidity fluctuations. Figure 2 illustrates the geophysical distribution of correlation exponents calculated from the relative humidity fluctuations of 73 stations over China, from which it can be found that the correlation exponent is small over the stations near the coastlines and south of China, but large over the stations north of China. There is no marked spatial characterization for different climate regions to draw further conclusion. Furthermore, it is obvious that the averaged scaling exponent ($\alpha = 0.75 \pm 0.07$) of the relative humidity fluctuations is higher than that ($\alpha = 0.64 \pm 0.06$) of the temperature fluctuations, so relative humidity fluctuations take on a different statistical behavior from other meteorological quantities, such as temperature [*Vattay and Harnos*, 1994].

[8] Here we emphasize that the long-memory process of the 73 stations over China's daily relative humidity records is characterized by the DFA scaling exponent $\alpha > 0.5$. So, the positive persistence in the past 50 years of one station's R-H record may imply a long-lasting persistence in the future. However, we can not determine the environmental situation of a certain area simply by the persistence of the humidity, the background must be considered also. In order

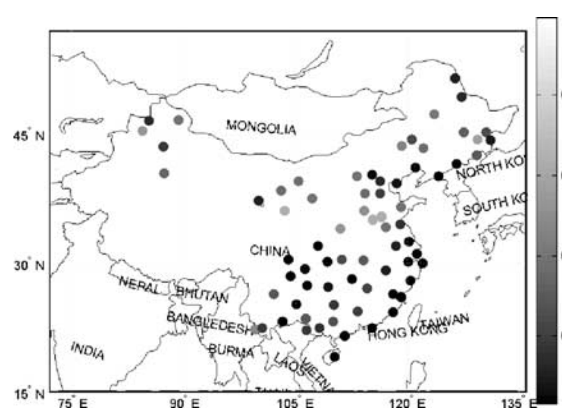

Figure 2. The geographical distribution of scaling exponents α of daily R-H for 73 stations over China.

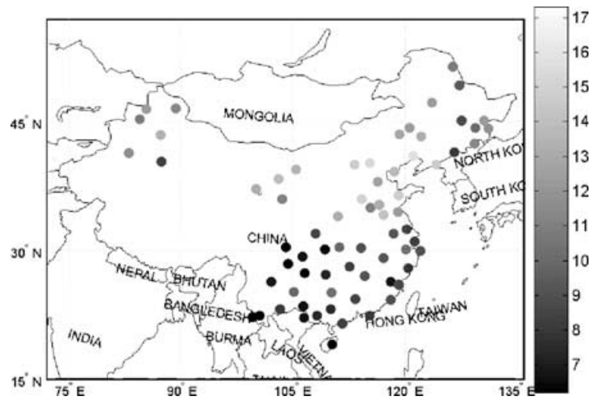

Figure 3. The geographical distribution of standard deviations σ of daily R-H for 73 stations over China.

to investigate the spatial distribution over different regions, we calculate the standard deviations σ'(in order to see the distinguished differences among different stations, we define $\sigma = 100\sigma'$) from each relative humidity anomaly time series for all 73 stations, and their spatial distribution is plotted as Figure 3, from which we can see that except for some specific stations, the standard deviation σ is larger over the northern midland of China but small over the southern midland of China, and there exist two transition areas to the east and west of midland (i.e. northeast and northwest of China) with no uniform feature.

[9] It is known that the southern part of China is more likely to suffer the regular influence of the monsoon, this main factor makes the fluctuations of the R-H anomaly records in the humid areas become small, and so the standard deviation σ is usually small in such stations. However, without the influence of the monsoon, factors that are weak in the south become major factors in northern China. These factors are usually variable, accompanied by climate extremes such as drought. After the seasonal trends are removed, the fluctuations of the R-H data are bigger which is characterized by the larger value of the standard deviation σ.

[10] So, to some extent, the standard deviation σ provides some information about background. For the government

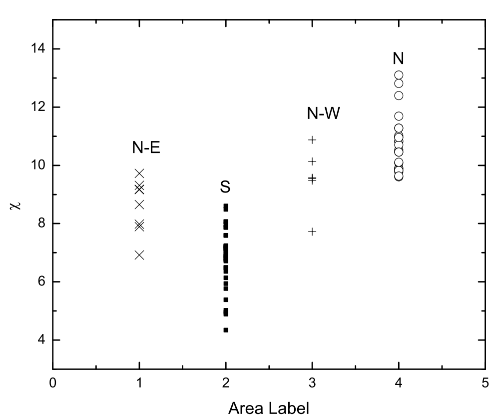

Figure 4. The value distribution of χ for daily R-H over midland of China, where the area label N for the northern midland of China, S for the southern midland of China, N–E and N–W for the northeast and northwest of China.

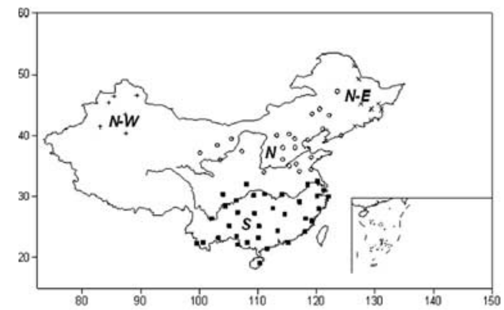

Figure 5. The geophysical distribution of χ for daily R-H over China, where the area label N for the northern midland of China, S for the southern midland of China, N–E and N–W for the northeast and northwest of China.

and the scientists, both aspects (persistence and background) need to be considered to well comprehend the climate situation of a certain area. However, from the scatter plot of the standard deviation of the relative humidity data fluctuations versus the scaling exponent observed from the same station(the figure is not shown here), we can not find the similar crowd or patch behaviors found in the temperature fluctuations over different climatic regions [*Kurnaz*, 2004].

[11] To better illustrate different characteristics over different climatic regions, we need introduce a new index χ which is defined by the scaling exponent α and standard deviation σ from a same data set, i.e. $\chi = \alpha\sigma$. It is easy to check that there is a distinct χ for the relative humidity fluctuations over the northern midland of China and over the southern midland of China, see Figure 4. Since we know that the northern Chinese midland is arid or semi-arid and the southern Chinese midland is humid, therefore χ values of 4.43 $\sim$ 8.61 represent the southern, humid areas and 9.60 $\sim$ 13.11 represent northern, arid or semi-arid areas, as Figure 5. Over the northeastern, χ is close to southern values, and over the northwestern stations, χ is closer to northern values. It is known that there are deserts in the northwest, and this area is of dry climate; also, the summer monsoon can move to the northeast and transport vapor to this area, so northeast should have similar climate characteristics as southern China. Figure 4 can therefore represent such properties to some extent. However, considering that the climate characteristics of these two transition areas (northeast and northwest), the value range of the northeast and northwest part is too close. It has been reported that the northwest of China became wetter and the northeast dries in last 50 years [*Zou et al.*, 2005]. So the transition intervals of χ may just correspond to these climate changes. We do not want to overemphasize this discussion on the transitional areas because the number of stations in these areas is too limited. Of course, deeper research is possible, and highly desired on this issue.

4. Conclusion and Discussion

[12] In this paper, we have studied daily R-H records of about 50 years for 73 weather stations over China using the DFA methods. It is obvious that the relative humidity fluctuations take on a different statistical behavior from other meteorological quantities and it is found that their

averaged scaling exponent is higher than that of temperature fluctuations. Also, to gain a better understanding of the climate situation of a certain area, both the trend and the status, marked by the scaling exponent α and the standard deviation σ, respectively, should be considered. So we introduce a new index χ which is defined by the two indices and find a striking delineation between different areas which have different climatical characters.

[13] **Acknowledgments.** Many thanks are due to support from National Natural Science Foundation of China (40305006) and special thanks to Sven Alef for helpful discussions.

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