SCALING BEHAVIOR OF GLOBAL MEAN SEA SURFACE TEMPERATURE ANOMALIES

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Abstract: Scaling behavior of the monthly global mean sea surface temperature (SST) anomalies from Kaplan SST V2 data are studied by multifractal detrended fluctuation analysis (MF-DFA) method. A crossover at time scale of 38 months (≈3.2 years) is identified to separate distinct regimes: small-scale and large-scale, indicating different patterns of scaling behaviors at different timescales. The scaling exponent $h(2)$=1.42 at the small-scale (e.g., <3.2 years), indicating the time series of SSTA is non-stationary and slightly anti-persistent, which may due to the El Niño/La Niña-Southern Oscillation (ENSO). At the large-scale (e.g., >3.2 years), $h(2)$=0.89, showing it is stationary and persistent. This property maybe related to the Pacific Decadal Oscillation (PDO). At the same time, the monthly global mean SSTA shows multifractality with the curves of $h(q)$, $\tau(q)$ and $D(q)$ depending on the values of q.

INTRODUCTION

To characterize the Sea Surface Temperature (SST) variability at temporal and spatial scales still poses a challenge to many researchers. Especially, while intense study focus on the low-frequency trends and components, however, few have approaches the problem of the high-frequency components, e.g., the scaling behavior and long-range correlation of SST anomalies. Long-range correlation (or long-term memory or persistence) in time series fluctuations refers to that the correlation functions exponentially decays over time and persists a significant value over a wild range of time (Beran 1992; Rangarajan 2003; Leung 2010). In another word, long-range correlation means that if an anomaly of a particular sign exists in the past it will most likely continue to exist in the future (Tsonis, Roebber et al. 1999). Long-range correlation have been found in many climatological and meteorological records including temperature, precipitation, air humidity, wind speeds (Kavasseri and Nagarajan 2004; Bunde, Eichner et al. 2005; Kantelhardt, Koscielny-Bunde et al. 2006; Rybski, Bunde et al. 2006; Chen, Lin et al. 2007; Lennartz and Bunde 2009; Zhou and Leung 2010; Zhu, Fraedrich et al. 2010; Mann 2011; Rea, Reale et al. 2011).

Temperatures of the atmosphere, the land surface and ocean surface have been showing long-range correlations. Monettia et al. (2003) found that the SST fluctuations display a non-stationary behavior for Atlantic and Pacific Oceans and their correlations are stronger than atmospheric land temperature fluctuations. However, they excluded those sites in the tropical Pacific region where the El Niño/La Niña-Southern Oscillation (ENSO) takes place (Monettia, Havlina et al. 2003). Fraedrich and Blender (2003) used a 1000-year simulation with a complex coupled atmosphere–ocean model to reproduce the observed scaling properties of atmosphere and ocean temperature. Alvarez-Ramirez et al. (2008) studied the long-term memory of temperature records for both Northern and Southern hemispheres, and their results confirmed more persistence in Ocean temperatures than land temperatures. It has also been suggested that the scaling exponent for island stations and sea surface temperatures is considerably higher than that of continental temperature (Bunde and Lennartz 2012). In general, scaling behaviors in SST series done by the previous studies focused at one whole timescale, the plausible differences between at different timescales and its multifractality are expecting more study.

Detrended Fluctuation Analysis (DFA) proposed by Pent et al. (1994) is a widely used approach to detect the fractal scaling properties of and the long-range correlations in time series (Peng, Buldyrev et al. 1994). An improved method based on the identification of the scaling of the q^{th}-order moments of the time series, the Multifractal Detrended Fluctuation Analysis (MF-DFA) (Kantelhardt, Zschiegner et al. 2002) can handle not only stationary time series but also non-stationary time series with unclear trend and noise (Hurst 1950; Kantelhardt, Zschiegner et al. 2002; Zhou and Leung 2010). The weather and climate system is a complex, dissipative, diabatic, nonlinear dynamic, the climate time series are generally nonstationary, and their statistics (average, variance, etc.) change with time. Hence MF-DFA is employed in this study.

The purpose of this study is to investigate the long-range correlation and multifractal scaling behaviors of the global SST anomalies (SSTA). Specifically, answers are sought in quantitative terms for the following issues: 1) Are the scaling behaviors of global SSTA time series different at different timescales? 2) Do SSTA series exhibit multifractality properties? To facilitate our analysis and discussion, we organize this paper as follows. We firstly introduce the dataset used in this study and the procedure of MF-DFA method. Then we will present the MF-DFA results of SSTA series and discuss with some interpretations. Conclusions will be given in the last section.

DATA AND METHODOLOGY

a. Data

The sea surface temperature (SST) dataset is obtained from Kaplan SST V2 data provided by the NOAA/OAR/ESRL PSD, Boulder, Colorado, USA, from their Web site at http://www.esrl.noaa.gov/psd/ (Kaplan 1998). This dataset is generated by taking the MOHSST5 version of the GOSTA dataset from the U.K. MET office as the input SST dataset to various processing steps, including Empirical Orthogonal Function projection, Optimal Interpolation, Kalman Filter forecast, Karl Fischer analysis, and an Optimal Smoother (Kaplan 1998). The global mean SST anomaly is calculated from the weighted averaged SSTA at each grid (5°×5°). The monthly anomalies from January 1856 to December 2011 are calculated based on the 1951-1980 time period (Reynolds 1994; Kaplan 1998). The time series of monthly global mean SSTA is shown in **Figure 1**.

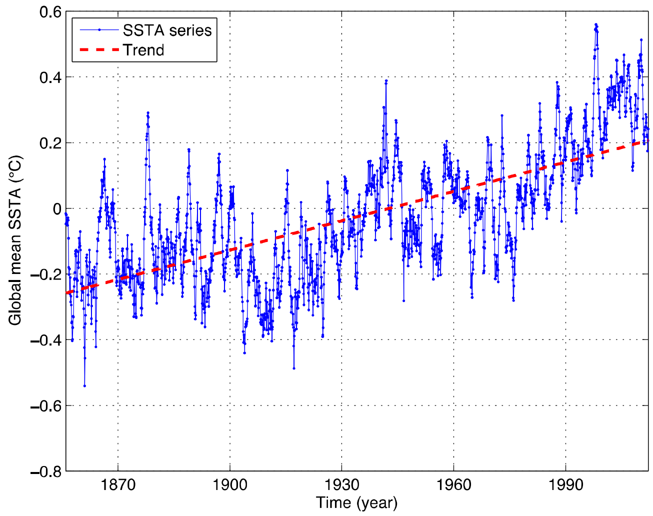


Figure 1. Monthly time series of global mean SSTA (unit: °C) from January 1856 to December 2011. An obvious warming trend in the global SSTA series is indicated in red dashed line.

b. Multifractal Detrended Fluctuation Analysis (MF-DFA)

In this study, we employ a recently developed technique, Multifractal Detrended Fluctuation Analysis (MF-DFA) (Kantelhardt, Zschiegner et al. 2002), to detect long-range correlations in SSTA time series. Suppose that x_k $(k = 1,2,\cdots,N)$ is a series of length N with, the procedure of MF-DFA methods is summarized as following steps (Kantelhardt, Zschiegner et al. 2002). First, we construct the 'profile' of the original time series. $Y(i) \equiv \sum_{k=1}^{i}[x_k - \langle x \rangle]$, $i = 1,2,\cdots,N$, where $\langle x \rangle$ is the mean values of $\{x_k\}$.The 'profile' is then divided into $N_s = \mathrm{int}(N/s)$ non-overlapping windows with equal length s. Hence, we can obtain $2N_s$ segments altogether. We then calculate the variance of local trend for each window:

$$\begin{cases} F^2(s,v) = \frac{1}{s}\sum_{i=1}^{s}\{Y[(v-1)s+i] - y_v(i)\}^2, & \text{for } v = 1,2,\cdots,N_s, \\ F^2(s,v) = \frac{1}{s}\sum_{i=1}^{s}\{Y[N-(v-N_s)s+i] - y_v(i)\}^2, & \text{for } v = N_s+1,\cdots,2N_s, \end{cases}$$

where $y_v(i)$ is the fitting polynomial representing the local trend in the vth window. Note that linear, quadratic, cubic, or higher-order polynomial $y_v(i)$ can be used in fitting the local trend. After that, through averaging over all windows, we obtain the q^{th} order fluctuation function:

$$F_q(s) = \left\{\frac{1}{2N_s}\sum_{v=1}^{N_s}[F^2(s,v)]^{q/2}\right\}^{1/q},$$

where q can be any real number, for $q = 2$ specially, the MF-DFA are actually traditional Detrended Fluctuation Analysis (DFA). If the time series follows the power law of $F_q(s) \propto s^{h(q)}$, then we can obtain the scaling function generalized Hurst exponent $h(q)$, which is then determined by the regression of $\log F_q(s)$ on $\log s$ in some range of time s. When $h(q)$ depends on the order of q, the time series is said to be multifractal; otherwise it is monofractal.

For stationary time series, $0<h(2)<1$, the exponent $h(2)$ for small timescales is identical to the well-known Hurst exponent H; while for the non-stationary time series, $1<h(2)<2$, the Hurst exponent is $H=h(2)-1$ (Hu, Ivanov et al. 2001). It is noted that, for the uncorrelated time series, the scaling exponent $H=0.5$; $0.5<H<1$ indicates long memory or persistence and $0<H<0.5$ indicates short memory or anti-persistence. As a results, we then can use $h(2)$ to determine whether a time series is stationary or non-stationary and detect its long-range correlation.

RESULTS AND DISCUSSION

The MF-DFA results are shown in **Figure 2**, the scaling behavior in SSTA exhibits a special crossover time scale at around 38 months (≈3.2 years), separating two distinct regimes: a small-scale within 3.2 years and a large-scale longer than 3.2 years. The crossover scale indicates different characteristics of scaling behaviors exist at different timescales. The crossover scale should correspond to the average period of El Niño/La Niña-Southern Oscillation (ENSO), which is a cyclic phenomenon warming the east equatorial Pacific Ocean every 3–6 year (Cane, Zebiak et al. 1986; Tziperman, Stone et al. 1994; IPCC 2007). At the same time, the time series of weekly SST in South China Sea shows a crossover time scale of 235 weeks (4.5 years) (Gan, Yan et al. 2007). A similar crossover time scale around 1066 days (2.9 years) has also been found in the daily time series of sea level in Hong Kong (Zhang and Ge 2012).

At the small-scale less than 3.2 years, as shown in **Figure 2**, SSTA series is non-stationary with its scaling exponent $h(2)$ is larger than 1. The fact that $h(2)$ is above 1 means that the variance of the SSTA fluctuations in a time window s increases as $s^{h(2)-1}$, i.e., as $s^{0.424}$ for timescales below 3.2 years. At this scale, the Hurst exponent $H = h(2) - 1 = 0.424 < 0.5$, indicating that the scaling behavior of SSTA changes to slightly anti-persistence. The anti-persistence in small-scale might be under the mechanisms of ENSO, in which El Niño (SST warming in central and eastern tropical Pacific) and La Niña (SST cooling in the central and eastern tropical Pacific) tend to occur alternately.

At the large-scale, on the other hand, the scaling exponent $h(2)$ is less than 1 ($h(2) = 0.897$ in **Figure 2**), indicating that SSTA series is stationary at the large-scale. The Hurst exponent of SSTA series is larger than 0.5, showing long-range memory or persistence, which means the variation of SSTA should maintain the same trend at the large-scale. This suggests that if an anomaly of a global SSTA exists in the past it will most likely continue to exist in the future at time scale larger than 3.2 years. This may reflect a distinct dynamic mechanism of SSTA under the Pacific Decadal Oscillation (PDO), which is characterized as warm or cool surface waters in the Pacific Ocean, each phases (warm or cool) generally persists 20-30 years (Mantua, Hare et al. 1997; Mantua and Hare 2002; Chavez, Ryan et al. 2003). A similar persistent correlations has been found exhibiting in the total ozone content for time scale between 4 and 90 years (Efstathiou, Tzanis et al. 2009).

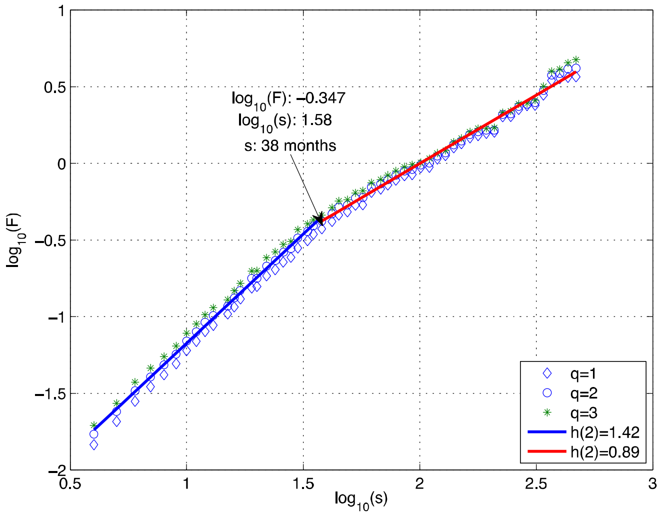
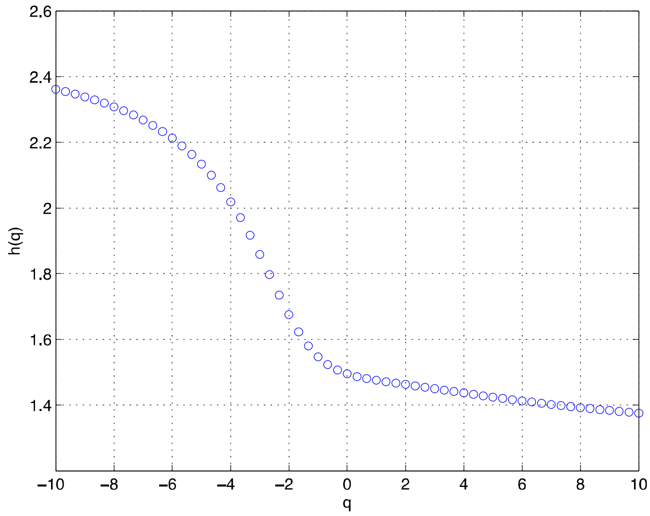
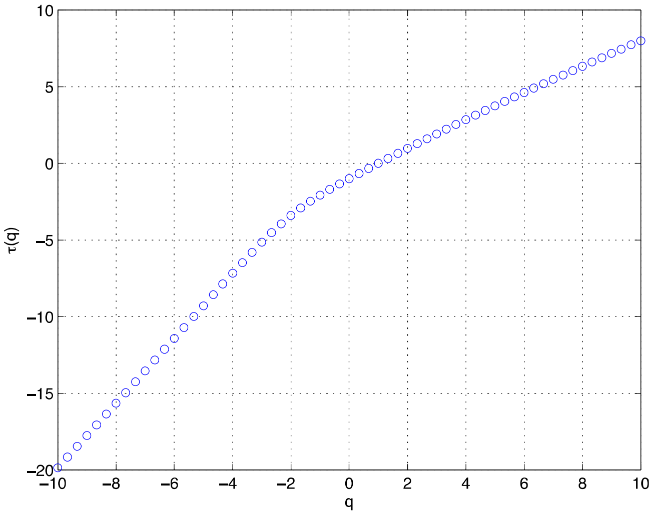


Figure 2. The log-log plots of $F_q(s)$ (q=1, 2, 3) versus s of the monthly global mean SSTA series. The crossover scaling point is around 38 months. The slopes of fitted lines represent the scaling exponents, $h(2)$.

To further detect the multifractal properties of the global monthly SSTA series, we analyze the dependence of the generalized Hurst exponent $h(q)$, mass function $\tau(q)$, and the generalized fractal dimension $D(q)$ on q (Grassberger and Procaccia 1983; Kantelhardt, Zschiegner et al. 2002). If the time series is multifractal, h(q) and $D(q)$ will vary with the change of q depicting fractal properties from different moments q, and τ(q) will be a nonlinear function of q. For monofractal time series, on the other hand, the value of $h(q)$ and $D(q)$ will not change with different moments and τ(q) will be a linear function of q, characterizing a single form of self-similarity over time. **Figure 3** (a), (b) and (c) show the dependence of $h(q)$, $\tau(q)$ and $D(q)$ respectively. All of these indicate that the global average SSTA series is multifractal. The property of multifractality suggests that the underlying global SSTA series was generated by nonlinear (fractal) stochastic processes with various interacting contributions (Alvarez-Ramirez, Alvarez et al. 2008). The multifractality of SSTA appears to be first discovered by this study.





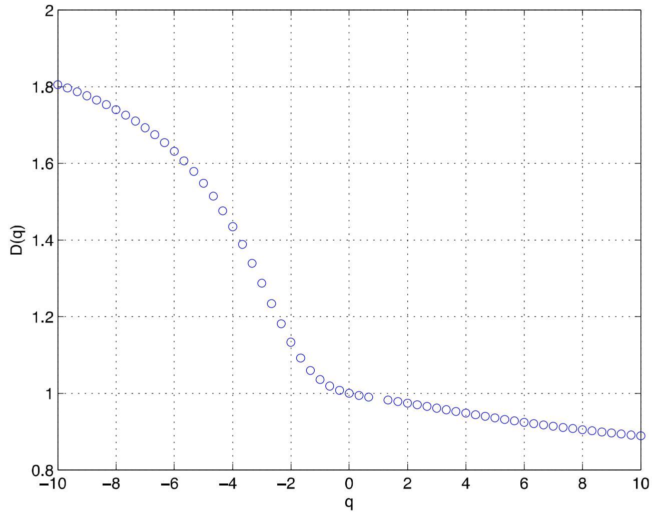


Figure 3. The $h(q)$, $\tau(q)$ and $D(q)$ curves of the monthly global mean SSTA series.

CONCLUSION AND DISCUSSION

As has been mentioned above, the purpose of this paper is to detect the long-range correlation and multifractal scaling behaviors of the global SSTA using MF-DFA approach, by which the result cannot be impacted by the trend of "global warming". Distinct from the previous studies for climatological time series, this study differentiates the scaling behaviors of SSTA anomalies at different timescales and looks into its multifractality.

Our results show that the monthly global average SSTA series are long-range correlated. A significant crossover at scale 3.2 years separates the timescale into two distinct parts: small-scale (e.g., < 3.2 years) and large-scale (e.g., > 3.2 years). The scaling property at first part shows as non-stationary series and is slightly anti-persitent. This scaling behavior might be under the mechanism of ENSO. While the scaling property at the large-scale shows strong long-term memory, and show as a stationary series, which maybe due to the PDO domination. The $h(q)$, $\tau(q)$ and $D(q)$ curves depends on the values of q, indicating the time series of global mean SSTA is multifractal.

Our analysis indicate that the persistence at large-scale is stronger than that at small-scale. Our finding is important to be able to evaluate decadal predictions and longer term climate change in a global scale. However, how the ocean-atmosphere interactions and circulations influence the SSTA variation and persistence need be studied further. It should be also noticed that, despite the presence of spectral peaks on decadal time scales and the strong persistence of SST variability, we cannot get satisfying prediction results in a long period (Newman 2007). There is still a long way to investigate the underlying mechanisms of SSTA variation and to obtain satisfying results of long-term prediction for SSTA.

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