Scaling Behaviors of Global Sea Surface Temperature

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(Manuscript received 2 December 2013, in final form 12 November 2014)

ABSTRACT

Temporal scaling properties of the monthly sea surface temperature anomaly (SSTA) in global ocean basins are examined by the power spectrum and detrended fluctuation analysis methods. Analysis results show that scaling behaviors of the SSTA in most ocean basins (e.g., global average, South Pacific, eastern and western tropical Pacific, tropical Indian Ocean, and tropical Atlantic) are separated into two distinct regimes by a common crossover time scale of 52 months (i.e., 4.3 yr). It is suggested that this crossover is modulated by the El Niño/La Niña–Southern Oscillation (ENSO), indicating different scaling properties at different time scales. The SSTA time series is nonstationary and antipersistent at the small scale (i.e., <crossover). It is, however, stationary and long range correlated at the large scale (i.e., >crossover). For both time scales, scaling behaviors of SSTA are heterogeneously distributed over the ocean, and the fluctuation of SSTA intensifies with decreasing latitude. Stronger fluctuation and stronger persistence are found in mid- and high-latitude areas, coinciding with the “reemergence” areas.

1. Introduction

Sea surface temperature (SST) is one of the most important parameters for the understanding of climate dynamics and climate change. Though SST can be easily measured, it is not always simple to analyze because of its irregular and nonlinear evolution across the temporal

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DOI: 10.1175/JCLI-D-13-00743.1

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In another words, 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. Long-range correlation exists in many climatological and meteorological records such as temperature and precipitation (Chen et al. 2007; Kantelhardt et al. 2006; Zhou and Leung 2010). Long-range correlations of temperature in the atmosphere, on land surfaces, and especially on ocean surfaces have attracted considerable attention because of their important influences on climate and the environment at global and regional scales. Monetti et al. (2003), for example, noticed that the SST fluctuations display a nonstationary pattern of behavior in the Atlantic and Pacific Oceans and their correlations are stronger than the 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.

Fraedrich and Blender (2003) used a 1000-yr simulation of a coupled atmosphere–ocean model to reproduce the scaling properties of atmosphere and ocean temperature. Rybski et al. (2008) compared the long-range correlation of 1000-yr temperature records in historical simulations and control runs for the daily and biannual resolutions. However, the question of how well the global climate models are able to reproduce the multifractal features of the climate system has not been addressed in their study. By examining the scaling exponent of seven global climate models, Govindan et al. (2002) argued that atmosphere–ocean general circulation models fail to reproduce the long-term memory for daily maximum temperature. Blender and Fraedrich (2003) examined the power-law exponents of near-surface temperature in the simulations of two models, HadCM3 and ECHAM4/OPYC, under the IS92a scenario, and compared them globally with the NCEP–NCAR reanalysis data. Alvarez-Ramirez et al. (2008) studied the long-term memory in temperature records in both the Northern and Southern Hemispheres, and confirmed that ocean temperatures are more persistent than land temperatures. It has also been suggested that the scaling exponents of monthly temperatures recorded at island stations and SSTs are considerably higher than those of the continental temperature (Fraedrich and Blender 2003). For daily temperature records, however, Bunde et al. (2004) showed that there is no significant difference between inland and coastal stations. In general, the scaling behavior in SST series obtained by current studies focuses on the whole time scale but its differences at different time scales have not been examined. Scaling behaviors of SST at different time scales must be investigated in order to have a deeper understanding of the dynamics involved.

It has also been shown that long-range correlations in weather and climate systems depend on geographical locations. For example, scaling exponents of daily temperature depend on altitude (Weber and Talkner 2001). Longitude is found to be the dominating factor determining the scaling exponents of land surface temperatures in Australia (Király and Jánosi 2005). Scaling behavior of SSTa over the South China Sea shows that long-range correlation is weaker in places near the coast and relatively stronger in places far from the coast (Gan et al. 2007). The long-term dependence of the global tropopause has also been found to be larger in the tropics than in the middle and high latitudes (Varotsos et al. 2009). However, the geographical dependence of the scaling behaviors in SSTa series on oceans around the globe as a whole is not revealed.

Detrended fluctuation analysis (DFA) proposed by Peng et al. (1994) has been a common approach used to detect the fractal scaling properties and long-range correlations. Differing from conventional fractal analysis, such as R/S (rescaled range) analysis, DFA handles not only stationary time series but also nonstationary time series with noise and trend. Because the weather and climate systems are complex, dissipative, diabatic, nonlinear, and dynamic, climate time series are generally nonstationary and their statistics change over time, DFA is thus employed in this study to unravel the temporal variability of SSTa.

The purpose of this study is to investigate the long-range correlation and multiscale behavior of the global SSTa variations. In particular, answers are sought in quantitative terms for the following questions: 1) Is the SSTa series self-similar and long range correlated over time? 2) Is there any specific periodicity, such as seasonal, annual, and decadal patterns in SSTa? 3) Are temporal behaviors of SSTa different in different parts of the oceans?

This paper is organized as follows. In section 2, we give a brief introduction of the DFA and spectral analysis methods employed in this study. Section 3 describes the dataset used in our analysis. Analysis results and their interpretations are made in section 4. Finally, we conclude the paper with a summary and outlook for further research in section 5.

2. Methodology

a. Power spectrum analysis (PSA)

One way of investigating the temporal scaling behavior of a time series is to calculate its power spectrum
density $S(f)$ using a Fourier transform (Beran 1994). The scaling exponent $\beta$ can be determined when a time series obeys a power law in the form of

$$S(f) \propto 1/f^\beta,$$

(1)

where $f$ is the frequency and $S(f)$ is the power spectrum density, which is expressed as

$$S(f) = \left[ N^{-1/2} \sum_{k=0}^{N-1} x_{k+1} e^{-2\pi i f k} \right]^2.$$  

(2)

A value of $\beta = 0$ indicates an uncorrelated time series (i.e., white noise), a value of $\beta = 1$ indicates $1/f$ or pink noise, and a value of $\beta = 2$ indicates brown noise.

b. Detrended fluctuation analysis

Detrended fluctuation analysis, as proposed by Peng et al. (1994), is also employed to study the scaling behavior of SSTAs, particularly their long-range correlation and geographical dependence. To facilitate our discussion, the generalized DFA procedure is briefly introduced as follows (Peng et al. 1994; Kantelhardt et al. 2001). Let $x_k (k = 1, 2, \ldots, N)$ be a series of length $N$ to which the procedure of the DFA method is applied. First, we construct the “profile” of the original time series:

$$Y(i) = \frac{1}{I} \sum_{k=i}^{i+I-1} (x_k - \langle x \rangle), \quad i = 1, 2, \ldots, N,$$

(3)

where $\langle x \rangle$ is the mean values of $x_k$. The profile is then divided into $N = \text{int}(N/s)$ equal-sized nonoverlapping windows with a length of $s$. Since $N$ is not the integral multiple of $s$ in most cases, there might be a short part at the end of the profile that remains uncovered. To take full account of the series, the same procedure can be repeated starting from the end of the series. Hence, we can obtain $2N_s$ segments altogether. We then calculate the variance of each window as

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

(4)

It should be noted that linear (i.e., polynomial order $m = 1$), quadratic (i.e., $m = 2$), cubic (i.e., $m = 3$), or higher-order polynomials $y_v(i)$ can be used to fit the local trend, and DFA is noted as DFA1, DFA2, DFA3, DFA4, etc. By averaging over all windows, we obtain the fluctuation function as

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

(5)

If the time series follows the power law, then we can obtain the scaling function:

$$F(s) \propto s^h.$$  

(6)

The fluctuation exponent (or generalized Hurst exponent) $h$ is then determined by regressing $\log F(s)$ on logs over some range of time scale $s$. In addition, $h$ is known as a fractal dimension, an index of complexity comparing how details in a fractal pattern change with the scale. It can be a noninteger value beyond the conventional Euclidean dimension, in which a point is zero dimensional, a line is one dimensional, and a cone is three dimensional in space.
3. Data description and processing

The monthly SST data used in this study are obtained from the Hadley Centre Sea Ice and Sea Surface Temperature dataset (HadISST) for the period from January 1870 to February 2012 (Rayner et al. 2003). This dataset is a combination of monthly globally complete fields of SST and sea ice concentration. Its spatial resolution is $1^\circ \times 1^\circ$, covering most parts of the global oceans. HadISST uses reduced space optimal interpolation applied to SSTs from the Marine Data Bank (mainly ship tracks) and ICOADS through 1981, as well as a blend of in situ and adjusted satellite-derived SSTs for 1982 onward (Rayner et al. 2003). In this study, the deseasonalized monthly anomalies are calculated by removing the climatological mean seasonal cycle during the period from 1961 to 1990.

To reveal the possible geographical heterogeneity in the world’s oceans, we focus on the following basins: eastern tropical Pacific, western tropical Pacific, North Pacific, South Pacific, tropical Atlantic, North Atlantic, South Atlantic, and tropical Indian Ocean. We exclude the Southern Ocean (Antarctic Ocean) and Arctic because of the limitations on data availability. As shown in Fig. 1, the division of ocean basins is modified based on Schlesinger and Ramankutty (1994), who have identified a multidecadal oscillation of 65–70 yr in the global surface temperature. Together with the global average, we derived nine time series of SSTA for scaling behavior analysis. The monthly time series of SSTA in the nine basins are presented in Fig. 2. Significant warming trends (at the 95% confidence level) and inter- and multidecadal variability are noticeable in all basins except for the eastern tropical Pacific, in which the SSTA series shows more interannual variability.

4. Results

a. PSA results

The power spectra $S(f)$ against frequency $f$ (i.e., month$^{-1}$) of the time series of SSTA in different oceans are depicted in Fig. 3. It can be observed that the power spectra of SSTA exhibit two regimes: higher and lower frequencies, suggesting that different scaling behaviors exist for high and low frequencies. Their differences are larger in the tropical oceans (e.g., tropical Pacific, tropical Atlantic, tropical Indian Oceans) than in the extratropical oceans (e.g., South and North Pacific, and South and North Atlantic). On the one hand, in the regime of lower frequency, $\beta$ values of PSA are smaller than 1 for all oceans, implying that the SSTA series are stationary and long range correlated. Compared with the extratropical regions such as the North Pacific ($\beta = 0.92$), South Pacific ($\beta = 0.97$), and South Atlantic ($\beta = 0.96$), SSTAs in the tropical regions such as the eastern tropical Pacific ($\beta = 0.22$), western tropical Pacific ($\beta = 0.74$), and tropical Indian Ocean ($\beta = 0.63$) have weaker long-range correlations. On the other hand, in the regime of higher frequency, $\beta$ values of PSA are larger than 1 and smaller than 2 for all oceans, showing a scaling behavior of nonstationarity and long-range anticorrelation. It can also be observed that $\beta$ in the tropical oceans (e.g., eastern tropical Pacific ($\beta = 1.81$), tropical Atlantic ($\beta = 1.76$), and tropical Indian Ocean ($\beta = 1.76$) are larger than in the extratropical oceans (e.g., North Pacific ($\beta = 1.41$), South Pacific ($\beta = 1.27$), and South Atlantic ($\beta = 1.23$)]. This implies that SSTAs in the tropical regions exhibit stronger fluctuations than in extratropical regions. It should be noted that, because of the strong fluctuation of the power spectra (see Fig. 3), the estimated slope (i.e., $\beta$) might be very uncertain and the crossover point is often not easy to identify. Hence, DFA is also employed for calculating the fluctuation exponents in SSTA. The results of DFA are discussed as follows.

b. Crossover time scale identified by DFA

To determine the order of DFA that would be able to estimate the value of $h$ and to identify the crossover time scale reliably, we use linear ($m = 1$, DFA1), square ($m = 2$, DFA2), and cubic ($m = 3$, DFA3) polynomial trends in the fitting procedure. The results are shown in Fig. 4. Though there are slight differences between the values of $h$ (and crossover points) for different $m$, DFA2 can appropriately reflect the scaling behaviors of SSTAs in our results, with only a slight difference from those of DFA1 and DFA3. In the literature, $m = 2$ is the most commonly used order for many geophysical signals (Peng et al. 1994; Lin et al. 2007; Witt and Malamud
Therefore, we use DFA2 to examine the scaling behaviors of SSTA series in the following analysis.

We first generate the log–log plots of \( F(s) \) versus \( s \) for SSTA time series in different basins. We then use an objective method, joinpoint regression, to determine the fluctuation exponent and to detect the plausible crossover time scale(s), and use the permutation test to examine whether the crossover time scale is statistically significant (Kim et al. 2000; Ge and Leung 2013). The analysis results are presented in Fig. 4. A crossover point at around 4.3 yr (=52 months) is found mainly in the global average and tropical basins, while it is located at around 2 yr in the extratropical regions (e.g., North Pacific, North and South Atlantic). The crossover points are similar to the results of PSA (see Fig. 3). The crossover time scale describes the crossover point at which the (multi-) fractal structure changes its behavior (Ge and Leung 2013). For example, the possible long-range correlations at a large scale of \( s > s_c \) may not exist at a small scale of \( s < s_c \) and vice versa, where \( s_c \) is the crossover time scale.

This crossover point corresponds to the cycle of El Niño/La Niña–Southern Oscillation, a 2–6-yr cyclical SST warming–cooling event in the tropic Pacific. During an ENSO cycle, El Niño (SST warming in the eastern tropical Pacific) and La Niña (SST cooling in the eastern tropical Pacific) tend to occur alternately. The most significant crossover time scale is given by the largest difference between values of the fluctuation exponent \( h \) at both small and large scales (i.e., \( h = 1.56 \) at small scale and \( h = 0.68 \) at large scale) in the eastern tropical Pacific, the place in which the ENSO event occurs. Compared with the eastern tropical Pacific, the global average and tropical SSTAs exhibit relatively smaller differences in \( h \) at small and large scales, showing a decaying crossover time scale that may be affected by an ENSO event. Apart from the crossover time scale identified in monthly SSTA time series, similar
Crossovers scales have also been found at daily sea level and weekly SST series (Gan et al. 2007; Zhang and Ge 2013). For instance, the time series of the weekly SST in the South China Sea shows a crossover time scale of 235 weeks (≈4.5 yr) (Gan et al. 2007). A similar crossover time scale at around 1066 days (≈2.9 yr) has been found in the daily time series of sea level in Hong Kong by Zhang and Ge (2013), who suggested that the crossover time scale is regulated by ENSO. As shown in Fig. 4, the crossover time scale separates distinct regimes that have different scaling behaviors at large and small scales.

### Long-range correlation

On the one hand, at the large scale, the fluctuation exponents $\hat{h}$ are less than 1 and larger than 0.5 (Fig. 4), indicating that the SSTA series are stationary and long range correlated. This finding suggests that the variation of SSTA maintains the same trend at the large scale: if a positive (negative) anomaly of SSTA existed in the past, we will most likely continue to have a positive (negative) anomaly in the future. In comparison with the global average ($\hat{h} = 0.78$) and SSTA in the extratropical regions such as the North Pacific ($\hat{h} = 0.83$), South Pacific ($\hat{h} = 0.95$), North Atlantic ($\hat{h} = 0.95$), and South Atlantic ($\hat{h} = 0.82$), SSTAs in the tropical regions, such as the eastern tropical Pacific ($\hat{h} = 0.68$), tropical Atlantic ($\hat{h} = 0.72$), and tropical Indian Ocean ($\hat{h} = 0.72$), have weaker long-range correlations. The extratropical SSTA reflects a distinct dynamic mechanism of SSTA under several long-term (e.g., interdecadal) oscillations such as the Pacific decadal oscillation (PDO) and the Atlantic multidecadal oscillation (AMO), while the tropical SSTAs show more complex structures. This long-range correlation pattern at large scale can also be observed from the results for lower frequency of PSA (see Fig. 3).
As shown in Fig. 4, SSTAs in the North Atlantic, South Atlantic, and North Pacific regions show a stronger long-range correlation. This implies that ENSO exerts less influence on SSTAs in these regions, compared with other tropical regions such as the tropical Indian Ocean and tropical Atlantic. The fluctuation exponents $h_1 = 0.95$ and $h_2 = 0.82$ for the North and South Atlantic, respectively, indicate that the extratropical Atlantic SSTAs exhibit a strong long-range correlation. This pattern is possibly modulated by AMO, which refers to the oscillation of the warming of the SSTs in the North Atlantic and the cooling in the South Atlantic with a period of 65–75 yr (Delworth et al. 1993; Kerr 2000). Under this modulation, SSTAs in the extratropical Atlantic maintain the same trend (e.g., warming or cooling) during one phase of the AMO, showing a long-range correlation. It is also observed that SSTAs in the North Atlantic have stronger long-range correlation than those in the South Atlantic (see Figs. 4 and 5). This finding agrees well with the fact that the AMO pattern is much more significant in the North Atlantic than the South Atlantic (Delworth et al. 1993; Kerr 2000). In addition, the fluctuation exponent $h_1$ is 0.86 in the North Pacific and 0.74 in the South Pacific, showing relatively weaker long-range correlation than in the extratropical Atlantic. The weaker long-range correlation is possibly related to the interdecadal period of 20–30 yr of the PDO pattern (see also Fig. 5), compared with the multidecadal period of 65–75 yr of AMO. Within a shorter period of time, the persistence of SSTAs in the extratropical Pacific is weaker than in the extratropical Atlantic.
On the other hand, at the small scale, for global average SSTAs and SSTAs in tropical oceans such as the tropical Atlantic, tropical Indian Ocean, and eastern and western tropical Pacific, the time series of SSTAs are nonstationary with the fluctuation exponents \( h \) larger than 1 (see Fig. 4). The fact that \( h \) is above 1 means that the variance of the SSTAs fluctuations within the time window \( s \) increases as \( s^{h-1} \). In addition, the times series of SSTAs is antipersistent because the Hurst exponent \( H = h - 1 < 0.5 \). This finding implies that a positive fluctuation of SSTAs in the past is more likely to be followed by a negative fluctuation in the future at this time scale, and vice versa. It is possible that the antipersistence at small scale is due to a mechanism affected by ENSO. During an ENSO cycle, an El Niño event (warming) and a La Niña event (cooling) tend to occur alternately, and this alternation can exert a large influence on most parts of the global ocean. For instance, ENSO can affect the SST in the tropical Indian Ocean and western tropical Pacific via the modification of the Walker circulation.

\[ \text{d. Geographical dependence} \]

To further understand the geography of the scaling behavior of SSTAs, we examine in detail the global distribution of long-range correlation in SSTAs series at small and large time scales. Figures 5 and 6 show the spatial distribution of the fluctuation exponent, \( h \), at large and small scales, respectively. It can be observed that the time series of SSTAs in most parts of the oceans are nonstationary and exhibit antipersistence at the small scale with \( 1 < h < 1.5 \). They become stationary and long range correlated (persistent) at the large scale with \( 0.5 < h < 1 \). This echoes the results depicted in Fig. 4. The relationship between the zonal average fluctuation exponent \( h \) and the latitude are shown in Fig. 7. With increasing latitude, the zonal average fluctuation exponent \( h \) at the small scale (close to crossover time scale) departs from 1.5, while \( h \) at the large scale (crossover time scale) comes closer to 1.0, indicating that persistence of SSTAs increases with increasing latitude, and so does the potential predictability of SSTAs. The fluctuation of SSTAs reaches its maximum near the equator where the strongest ocean–atmosphere interaction takes place. It is consistent with the results obtained by Zhu et al. (2010), who noticed a higher predictability in high-latitude oceans. Such higher predictability more distinctly represents the Northern Hemisphere, particularly in the subpolar Atlantic and the subpolar Pacific. However, the predictability of the surface temperature over land declines with increasing latitude and is relatively lower over the mid- to high-latitude continents (Boer 2011). This finding suggests that the mechanisms of surface temperature variations over land and sea are different.

Within the small scale, the correlation between the spatial pattern of the fluctuation exponent and the SST pattern associated with the Niño-3.4 index is 0.6.
significant at the 99.9% confidence level. The significant correlation indicates that scaling behavior of SST within the crossover time scale is mainly modulated by the ENSO cycle; this finding supports the statement that the crossover time scale is mainly modulated by the ENSO cycle. The strongest SSTA fluctuation at both time scales and the largest difference of $h$ between the two time scales occurring in the ENSO area (i.e., central-eastern tropical Pacific) support the idea that the crossover scale is linked to the ENSO cycle. At the same time, SSTA fluctuation in the low-latitude region (e.g., equatorial region) is larger than that in the region of higher latitude. This spatial pattern well agrees with the study by Fraedrich and Blender (2003), except that the magnitude of the fluctuation exponent is different from ours. The reason is that in our study the time scale is divided into two by the crossover time scale, and two different fluctuation exponents are identified; however, Fraedrich and Blender (2003) did not separate possibly different scaling behaviors over different time regimes.

Regardless of small or large scales, strongest fluctuations appear particularly in the central-eastern tropical Pacific Ocean, where the Hurst exponents ($H = h - 1$ for $h > 1$) are close to 0.5. This indicates that SSTA variations in this region are extremely volatile and distinguishable. It is the region with noticeably strong atmosphere–ocean interaction where ENSO takes place. The predictability of SSTA largely hinges on the ocean–atmosphere interaction in the tropical Pacific (Chen and Cane 2008), and it is affected by atmospheric disturbances interacting with the Southern Oscillation, particularly by the so-called westerly wind burst (Fedorov et al. 2003). Thus, ENSO is a highly damped oscillation sustained by stochastic forcing. In addition, as a self-sustaining interannual fluctuation in the tropical Pacific, it is chaotic but deterministic (Jin et al. 1994), and the tropical Indian and Atlantic Oceans can also influence the dynamics and predictability of ENSO (Frauen and Dommenger 2012). These forcings intensify the variability and fluctuation of SSTA in the ENSO region, making the scaling behavior unstable. It is observed in Fig. 5 that the north Indian Ocean and South China Sea (SCS) are the areas with strong fluctuations at both small and large time scales. The plausible reason is that interannual variability of these regions is closely associated with ENSO through the Walker circulation, and the ocean–atmosphere interaction is also very strong in this area (Wang et al. 2000). Two noticeable regions with $h > 1.4$ coincide more or less with the Niño-3 region (5°N–5°S, 150°–90°W) and the Niño-4 region (5°N–5°S, 160°E–150°W), respectively.

Smaller values of the fluctuation exponents at the small scale and larger values at the large scale appear in midlatitude regions, especially in the mid- and high-latitude Atlantic Ocean, western North Pacific Ocean, and Mediterranean Sea. This indicates that stronger persistence and long-range correlation exist in these regions. These regions correspond to the regions of “reemergence,” which is described as the mechanism through which the SSTA that formed in late winter is “isolated” underneath the relatively shallow summer mixed layer and then “reentrained” into the deepening mixed layer during the following winter or autumn (Deser et al. 2003; Hanawa and Sugimoto 2004). The reemergence mechanism can enhance the persistence of SSTA in some regions by more than a year. Several studies have shown that reemergence occurs in the North Pacific (Sugimoto and Hanawa 2005), North Atlantic (Watanabe and Kimoto 2000), Northern Hemisphere oceans (Deser et al. 2003), and the extratropical Southern Hemisphere (Ciasto and Thompson 2009).

Using five different SST datasets to detect reemergence areas in the global oceans, Hanawa and Sugimoto (2004) found seven reemergence areas: four in the Northern Hemisphere (the northern and southern North Pacific and the northern and southern North Atlantic) and three in the Southern Hemisphere (the south Indian Ocean, the South Pacific near southeastern Australia, and the South Atlantic). These areas correspond closely to our results shown in Figs. 5 and 6. Our analysis suggests that SSTAs in these areas exhibit reemergence and long-range correlation at both small and large time scales.

5. Conclusions and discussion

SST fluctuations exert a profound impact on climate at interannual to decadal time scales. It is of great significance to study the scaling properties and persistence of SSTAs in order to understand the mechanisms of SSTA variations and to improve the predictability of SST and relevant climatic phenomena. This paper has detected the long-range correlation and scaling behaviors of the global SSTA fluctuation using the PSA and DFA methods.

Differing from existing studies on climatic time series, this report differentiates among the scaling behaviors of SST anomaly at different time scales. By examining SST in different ocean basins, our analysis indicates that the persistence at large scale is stronger than that at small scale. Such a finding is important for the evaluation of decadal predictions and longer-term climate changes at the global scale. Our analysis results show that a significant crossover time scale occurred at the 52-month scale (4.3 yr) for the global average SSTA and tropical oceans. This crossover time scale separates SSTA into two distinct regimes, small scale (<crossover) and large scale
SST variations arise from different mechanisms, such as the local response to the stochastic atmospheric heat flux or advection of heat by the ocean circulation (Battisti et al. 1995). Possible dynamic mechanisms include coupled ocean–atmosphere oscillatory modes randomized by stochastic forcing, damped oscillatory modes of the ocean excited by atmospheric stochastic forcing, or self-sustained ocean, coupled modes and delayed oscillators (Griffies and Bryan 1997). The ways in which ocean–atmosphere interactions and circulations influence SSTA variability and persistence needs to be further studied.

Acknowledgments. This research was supported by the Geographical Modeling and Geocomputation Program under the Focused Innovation Scheme of The Chinese University of Hong Kong, the National Basic Research Program (973 Program) of China (Grant 2012CB955800).

REFERENCES


——, M. A. Alexander, C. Deser, and M. H. England, 2011: On the persistence of cold-season SST anomalies associated with the