On the Long-Term Climate Memory in the Surface Air Temperature Records over Antarctica: A Nonnegligible Factor for Trend Evaluation

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ABSTRACT

In this study, observed temperature records of 12 stations from Antarctica island, coastline, and continental areas are analyzed by means of detrended fluctuation analysis (DFA). After Monte Carlo significance tests, different long-term climate memory (LTM) behaviors are found: temperatures from coastal and island stations are characterized by significant long-term climate memory whereas temperatures over the Antarctic continent behave more like white noise, except for the Byrd station, which is located in the West Antarctica. It is argued that the emergence of LTM may be dominated by the interactions between local weather system and external slow-varying systems (ocean), and therefore the different LTM behaviors between temperatures over the Byrd station and that over other continental stations can be considered as a reflection of the different climatic environments between West and East Antarctica. By calculating the trend significance with the effect of LTM taken into account, and further comparing the results with those obtained from assumptions of autoregressive (AR) process and white noise, it is found that 1) most of the Antarctic stations do not show any significant trends over the past several decades, and 2) more rigorous trend evaluation can be obtained if the effect of LTM is considered. Therefore, it is emphasized that for air temperatures over Antarctica, especially for the Antarctica coastline, island, and the west continental areas, LTM is nonnegligible for trend evaluation.

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1. Introduction

In the context of global warming, assessment of Antarctic temperature change has become a very important issue during the past few years because of the impact that temperature changes may have on land/sea ice changes (Pritchard et al. 2012; Joughin et al. 2012). Based on measurements from regular weather stations and satellite and reanalysis data, temperature trends have been discussed both locally and for the whole continent (Comiso 2000; Marshall 2002; Vaughan et al. 2003; Turner et al. 2005; Monaghan et al. 2008). One well-recognized fact is that the Antarctic Peninsula has been found to be one of the most rapidly warming locations on Earth. This significant warming covers most of West Antarctica (Turner et al. 2005; Thomas et al. 2009; Schneider et al. 2012; Bromwich et al. 2013), whereas in East Antarctica the temperature change seems to be not so remarkable (Steig et al. 2009; Nicolas and Bromwich 2014).

When investigating the possible temperature change in the Antarctic, one main challenge comes from the paucity of surface observations. Even though more and more weather stations have been founded recently, the number is still small and most of them are located near the coast, providing little direct information about the continental interior. Therefore, the very first thing when discussing the temperature changes over the Antarctic is normally to get a reliable dataset, which can provide us with more information. Many efforts have been made during the past years, such as spatial reconstructions made by interpolating the sparse meteorological records (Steig et al. 2009; O'Donnell et al. 2011), as well as the temporal reconstructions made by infilling gaps with global reanalysis data, automatic weather station (AWS) data, and the satellite data (Bromwich et al. 2013; Nicolas and Bromwich 2014). Thanks to these efforts, a rough picture of how the temperatures over Antarctic change during the past decades has been formed, even though the magnitudes are still inconsistent among different researches.

With these reconstructions, the most widely discussed topic is whether the Antarctic is undergoing a significant temperature change (Bromwich et al. 2013; Bunde et al. 2014; Bromwich and Nicolas 2014). Normally, traditional statistical methods such as a Student's t test or autoregressive model of first order (AR1) are applied to rule out the possible temperature-change intervals owing to statistical noises or autocorrelations (Santer et al. 2000; Bromwich et al. 2013). However, besides these estimations, it is important to emphasize that another concept, long-term climate memory (LTM), should also be taken into account (Koscielny-Bunde et al. 1998; Malamud and Turcotte 1999; Lennartz and Bunde 2011). Long-term memory, or long-term persistence (correlations), is not a new concept. Actually, it has been proposed ever since the middle of the last century, and is thought to be ubiquitous in nature as the Hurst phenomenon (Hurst 1951). But extensive researches on LTM only emerged recently after several well-developed methods were introduced, such as the well-known wavelet analysis (WA; Arneodo et al. 1995) and detrended fluctuation analysis (DFA; Peng et al. 1994). Compared with traditionally short-term correlations, long-term memory, as its name implies, means that the autocorrelations can last for a very long time. From a statistical point of view, if a time series is characterized by LTM, its autocorrelation function will not decay exponentially with time lags but rather decays by a power law, as $C(n) \sim n^{-\gamma}$, where n is the time lag and $C(n)$ represents the autocorrelations (Kantelhardt et al. 2001). Therefore, theoretically the autocorrelations will never reach zero. In this case, large values well above the average are more likely to be followed by large values, while small values are followed by small values, and finally the time series are shaped as mountain and valley structures (Lennartz and Bunde 2009a; Franzke 2012; Becker et al. 2014). As shown in Fig. 1, this kind of structure of course will influence our estimation of significant trends (Lennartz and Bunde 2009a, 2011) and therefore needs our special attention. It has been reported that worldwide surface temperature records are normally long-term correlated, but with different strengths at different regions. Over ocean, the temperatures are found to be characterized by strong LTM; over coastal regions, the detected LTM becomes a little weaker; and over the inner continent, the LTM properties in surface temperatures are found to be the weakest (Fraedrich and Blender 2003; Blender and Fraedrich 2003; Eichner et al. 2003). Up to now, most of the studies had been done for regions where high-quality observations are available. However, for Antarctica, few studies have been published over the past years (Franzke 2010; Bunde et al. 2014). Considering that LTM is an important factor that needs to be taken into account when evaluating the significance of temperature changes, a careful diagnosis as to whether temperature over Antarctica is long-term correlated or not is an urgent task. In this study, we will focus on this so-called long-term memory for a variety of Antarctic stations covering the past (mainly) 50 years.

This paper is organized as follows. In section 2, we make a brief introduction of the data and provide a detailed discussion of the method we apply. Detailed diagnostic results on whether the temperature over Antarctica is long-term correlated or not are shown in section 3. In section 4, we provide further discussion on 1) how to understand the different LTM behaviors found in section 3 and 2) how the LTM may affect the trend evaluation. In section 5, we conclude this paper.

2. Data and methodology

a. Data

In this study, we analyzed monthly temperature records from 12 stations. The data (except the records from Byrd station) are mainly downloaded from the Reference

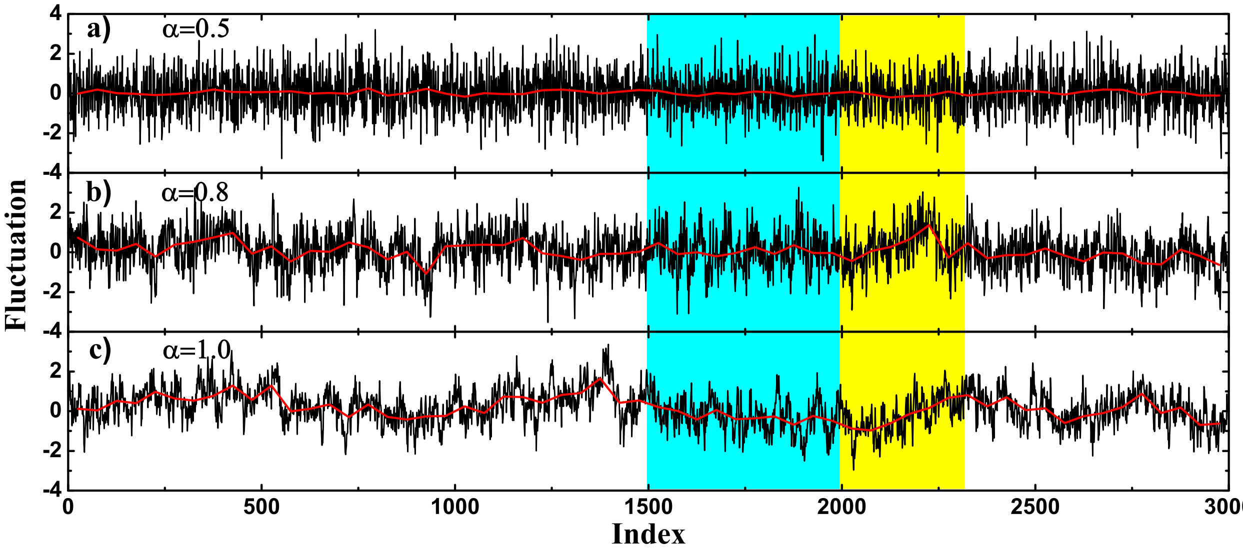

FIG. 1. Time series with different long-term memory: (a) white noise without LTM (DFA exponent $\alpha = 0.5$), (b) time series with strong LTM (DFA exponent $\alpha = 0.8$), and (c) time series with even stronger LTM (DFA exponent $\alpha = 1.0$). All the three time series are artificially generated without any external trends. However, owing to the existence of LTM (see the blue and yellow regions), internal trends arise in (b) and (c). When estimating trends of a given climatic variable, such as temperature, it is therefore necessary to take the effect of LTM into account.

Antarctic Data for Environment Research (READER) dataset (http://www.antarctica.ac.uk/met/READER/surface/), while the records from Byrd are obtained from the Byrd Polar Research Centre (http://polarmet.osu.edu/datasets/Byrd_recon/). We choose these 12 stations according to two criteria: 1) the observed temperature records should be relatively long, with few missing points, and 2) the stations should represent different specific regions of Antarctica, including coastal regions, the inner continent, and islands, as well as both East and West Antarctic. Locations of these 12 stations are shown in Fig. 2, with their altitude and data length explained in Table 1.

Although only a few stations are available, compared to model data or reconstructed spatial data the observational data are more reliable in providing information on LTM. It should be noted that the data from Byrd are also a reconstruction by Bromwich et al. (2013), but considering that the data have been proved to have high quality, and this is the only long observation over west Antarctic, we choose these data for our analysis.

Before analysis, we first remove the effect of periodic annual cycle, as suggested by many previous works, by $\tau_i = T_i - \langle T_i \rangle$ (Koscielny-Bunde et al. 1998); T_i represents the monthly temperature record, $\langle T_i \rangle$ is the annual cycle calculated from each calendar month, and τ_i is the temperature anomalies we use for the analysis.

b. *Methodology*

To diagnose whether a time series is characterized by LTM, there are several methods available, including the autocorrelation analysis, power spectral density (PSD) analysis (Talkner and Weber 2000), structure function method (Lovejoy and Schertzer 2012), and wavelet analysis (Arneodo et al. 1995), as well as methods based on random walking theory, such as the rescaled-range (R/S) analysis (Hurst 1951), fluctuation analysis (FA; Peng et al. 1992), and the detrended fluctuation analysis (Peng et al. 1994; Kantelhardt et al. 2001). Among all these methods, calculating autocorrelation coefficients is the most straightforward way, but it suffers from strong finite size effects at large time scales (Lennartz and Bunde 2009b). PSD has relatively better statistics than the autocorrelation analysis, but still needs special estimators [e.g., the Geweke–Porter-Hudak (GPH) estimator] to guarantee the fitting accuracy (Geweke and Porter-Hudak 1983; Vyushin and Kushner 2009). Structure function method, R/S analysis, and the standard fluctuation analysis FA are all designed for stationary time series, which are claimed not appropriate for time series with external trends mixed (Koscielny-Bunde et al. 1998, 2006; Bashan et al. 2008). Finally, only the WA and DFA can both provide better statistical outputs and are capable in dealing with nonstationary data (Arneodo et al. 1995; Kantelhardt et al. 2001). Compared with WA, the algorithm of DFA is easier for computational purposes; therefore, DFA has become the most widely used method in analyzing LTM. In this study, we also choose to use this method.

Suppose we have a record $\{x_i\}$. In DFA, one usually does not analyze the original record $\{x_i\}$ directly, but considers the cumulated sum (profile) $Y_j = \sum_{i=1}^{j} x_i$. After

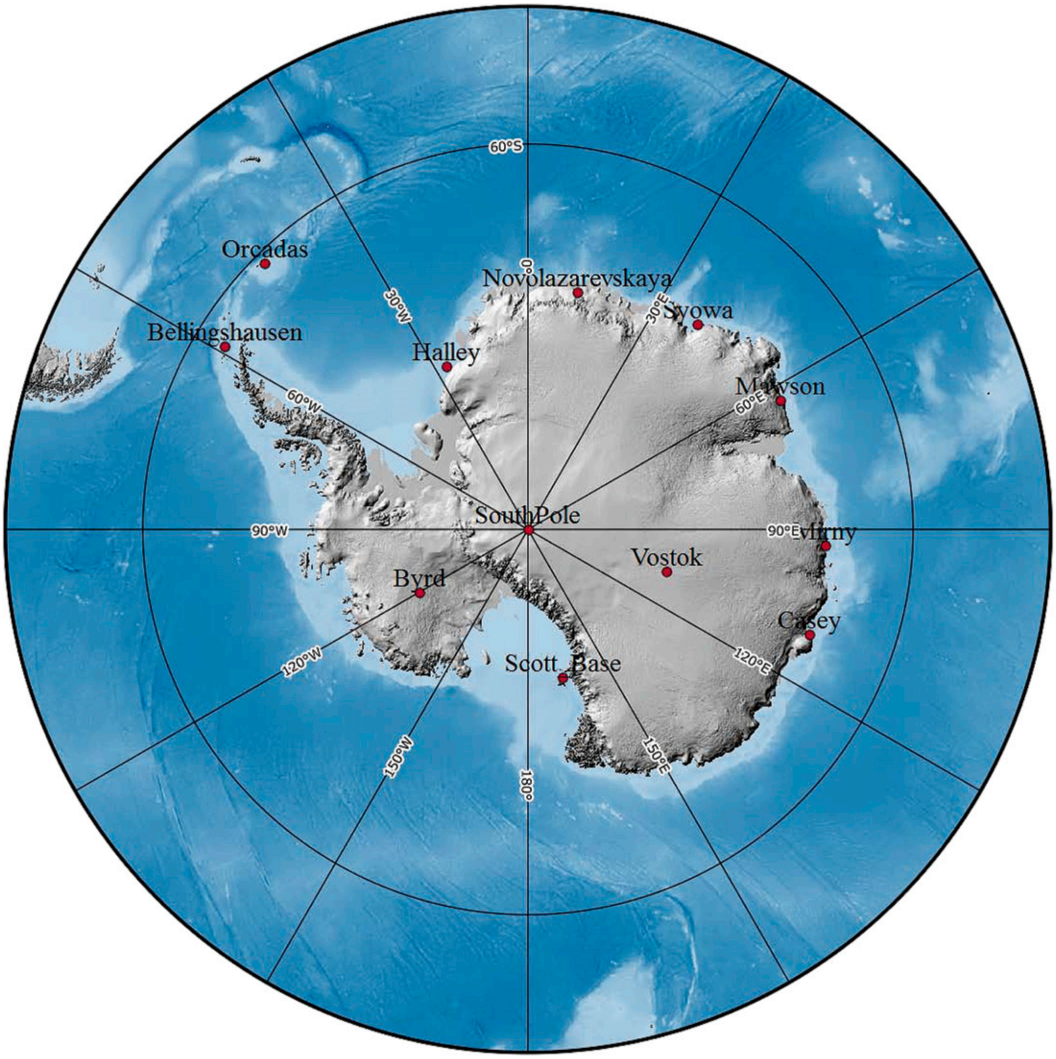

FIG. 2. Locations of the 12 stations. Six of them (Halley, Syowa, Mawson, Casey, Scott Base, and Bellingshausen) are built along the coastline (CS), two of them (Bellingshausen and Orcadas) are located in small islands (IS), and the last four (South Pole, Vostok, Novolazarevskaya, and Byrd) are classified as Antarctic continental stations (ACS).

dividing the profile into Ns nonoverlapping segments of size s (where $\mathrm{Ns} = [N/s]$), in each segment ν, the "local trend" $\widetilde{Y_{j,\nu}}$ will be polynomially fitted with variable orders. Normally, quadratic polynomial fitting is enough for the accurate estimation of LTM in temperature records, so in this study we choose to use the quadratic polynomial fitting, and the method can be denoted as DFA-2 (Kantelhardt et al. 2001).

With the local trend fitted in each segment ν, one can determine the "detrended walk" as the difference between the original profile $Y_{j,\nu}$ and the local trend $\widetilde{Y_{j,\nu}}$, and further calculate the variance as

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

The detrended fluctuation function is thus defined as

$$F_{\mathrm{DFA}}(s) \equiv \sqrt{\frac{1}{\mathrm{Ns}}\sum_{\nu=1}^{\mathrm{Ns}} f^2_{\mathrm{DFA}}(s,\nu)}, \qquad (2)$$

where Ns is the number of the windows, and $\nu = 1, 2, 3, \ldots, \mathrm{Ns}$. If $F_{\mathrm{DFA}}(s)$ increases by a power law, $F_{\mathrm{DFA}}(s) \sim s^{\alpha}$, with the exponent $\alpha > 0.5$, then the record $\{x_i\}$ is long-term correlated. If $\alpha < 0.5$, the record $\{x_i\}$ is considered as long-term anticorrelated. As for white noise with no autocorrelation, $\alpha = 0.5$. Therefore, the exponent α is considered as a measurement of LTM (Kantelhardt et al. 2001).

Note that as DFA is based on the random walking theory, one may find it not straightforward in describing

TABLE 1. Detailed information about the 12 monthly records used in this study, including the names of the stations, classifications, and their altitudes, beginning years, ending years, and the length.

Station	Group	Altitude	Begin	End	Length
Halley	Coastline station (CS)	30 m	1957	2013	57 yr
Syowa		21 m	1967	2013	47 yr
Mawson		16 m	1955	2013	59 yr
Mirny		30 m	1956	2013	58 yr
Casey		42 m	1960	2013	54 yr
Scott Base		16 m	1958	2008	51 yr
Bellingshausen	Island station (IS)	16 m	1969	2013	45 yr
Orcadas		6 m	1904	2001	98 yr
South Pole	Antarctic continental station (ACS)	2835 m	1957	2013	57 yr
Vostok		3490 m	1958	2013	56 yr
Novolazarevskaya		119 m	1962	2013	52 yr
Byrd		1515 m	1957	2013	57 yr

temporal variability of a given record. Therefore, we further introduce the Fourier transform–based method, power spectral density analysis, for better understanding. PSD analysis is a conventional and well-known method to characterize the fractal properties (or LTM) of time series (Talkner and Weber 2000). To determine the power spectral density $S(f)$, one first calculates the autocorrelation $C(n) = \langle [x(t+n) - \langle x \rangle][x(t) - \langle x \rangle] \rangle / \sigma^2$ of the signal, where n is the time lag and σ its variance. With $C(n)$, we can get $S(f)$ by Fourier transform. If the autocorrelation shows a scaling behavior (power law) for time scales larger than n, one can also find a scaling behavior (power law) of the power spectrum in corresponding frequency region $f < 1/n$. For long-term correlated time series, with increasing frequency f, $S(f)$ decays by a power law, $S(f) \sim f^{-\beta}$, where β characterizes the fractal properties (or LTM) of the considered time series. Compared with the power-law autocorrelation function $C(n) \sim n^{-\gamma}$, it can be derived easily that $\beta = 1 - \gamma$. When compared with the DFA exponent α, one can also find a one-to-one relationship between β and α, as $\beta = 2\alpha - 1$ [for detailed discussion, please refer to Talkner and Weber (2000)]. Since $S(f)$ describes the variabilities of given time series on different time scales (or frequencies), its power-law behavior thus indicates the links (or similarities) among different time scales. Obviously, with greater slope (in a log–log plot, as shown in Fig. 3b), bigger β will be fitted and stronger links will occur. From $\beta = 2\alpha - 1$, by analyzing the same time series, a larger DFA exponent α will also be found (as shown in Fig. 3a), which means a stronger LTM (or links from small time scales to large time scales). Note that for long-term correlated time series with $\alpha > 0.5$ and $\beta > 0$, higher energy is allocated to lower frequencies (see Fig. 3b), which indicates larger-scale structures, or in other words, more remarkable low-frequency variability of the considered time series (Yuan and Fu 2014), as shown in Figs. 1b,c and 3c. We then come back to the question discussed in the introduction, which is about the ''trend evaluation'' in time series with LTM.

We take the temperature anomalies over Byrd station as an example, and show both the DFA-2 and PSD results in Fig. 3. From the fitted exponents (α and β), one can see the relation between them is indeed $\beta = 2\alpha - 1$. From Fig. 3c, low-frequency variability along with some possible so-called local trends (the gray area) are presented in the temperature anomalies.

However, compared with DFA-2, there are two main limitations in PSD analysis. First, PSD is based on the Fourier transform, which assumes that the time series analyzed are stationary. If the considered variable is affected by external trends, or some other nonstationary factors, biased estimation of β will be obtained. Second, as shown in Fig. 3b, when fitting the exponent β, large errors are inevitable due to the enormous variations in the low frequencies. By using power-law estimators, such as the Geweke and Porter-Hudak (GPH) semiparametric estimator used by Franzke (2010), the uncertainties can be controlled, but more computational cost will also be required. Therefore, PSD normally is not the primary choice for LTM analysis.

In this study, we choose DFA-2. Before showing the results, we also note that, even for DFA-2, there are still criticisms that require our attention. First, on small time scales (normally $s < 10$), there is an unavoidable finite-size effect. This defect was first reported in the original reference (Peng et al. 1994) and emphasized by subsequent articles (Bryce and Sprague 2012; Shao et al. 2012). To avoid being affected by this effect, we only focus on the scaling range from $s = 12$ months (1 yr) to $s = 120$ months (10 yr) in our study. Second, on large time scales, the detrending procedure in DFA may have variable fidelity for different segment sizes, especially when unknown nonlinear trends exist in the data of interest (Bryce and Sprague 2012). In this case, biased DFA exponent α may be obtained. To avoid this risk, we

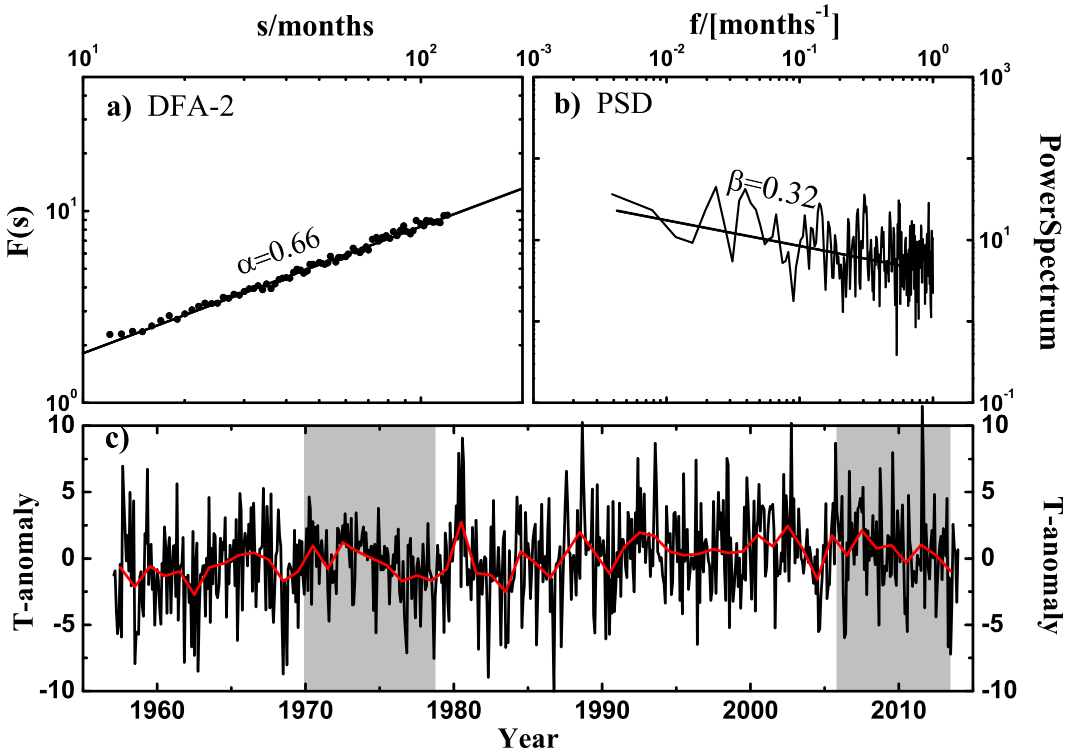

FIG. 3. Illustration of DFA-2 and PSD analysis, taking temperature anomalies over Byrd station as an example. (a) The DFA-2 result, where we find the exponent $\alpha = 0.66 \pm 0.01$, indicates that the temperatures over Byrd should be characterized by LTM. This exponent agrees, within the error bar, with earlier results by Bunde et al. (2014). (b) The PSD result, where we find the exponent $\beta = 0.32 \pm 0.05$. The fitted exponents α and β indeed obey the relation $\beta = 2\alpha - 1$. (c) The temperature anomalies. One can find trends in certain time intervals (the gray area), but it is difficult to tell whether the trend is induced by external forcing or should be ascribed to the existence of LTM.

employ Monte Carlo tests to ensure the accuracy of our judgment. For more discussion of the methods, please refer to Bryce and Sprague (2012) and Shao et al. (2012).

3. Results

In this study, we focus on the Antarctic region, where little attention was paid before. In fact, by using climate model simulated data, Rybski et al. (2008) discussed LTM properties globally, with Antarctic included. They found that the 2-m temperatures are long-term correlated in West Antarctica with DFA-2 exponent α around 0.725, whereas in the east it is less obvious with α around 0.575 [see Fig. 2a in Rybski et al. (2008)]. However, to tell whether the temperatures over one region are characterized by LTM or not, only using model simulated data is not enough since the ability of climate models to reproduce the correct LTM is still in question (Vyushin et al. 2004; Bromwich and Nicolas 2014). Recently, with observational data, Franzke (2010) characterized the LTM properties over eight Antarctic weather stations using the GPH semiparametric estimator (Geweke and Porter-Hudak 1983; Vyushin and Kushner 2009). Although the GPH estimator can provide a reliable power-law fit with acceptable uncertainties, it is actually an estimating method based on spectral analysis, which therefore may lead to biased estimations when external trends, such as the possible anthropogenic warming trend, exist. Meanwhile, the eight stations are mainly located along the coastline and nearby islands, with only one station (South Pole) located in the interior of the Antarctic continent. Therefore, as pointed out by Bromwich and Nicolas (2014), it is still not clear whether the temperatures over Antarctic are significantly long-term correlated. Since LTM is an important factor that needs to be taken into account when evaluating the significance of temperature trends over Antarctica, a detailed study on this issue is very necessary.

According to Fig. 2 and Table 1, one can see that among the 12 stations in our study, six of them are located along the coastline with low altitudes (<50 m), two are located on small islands with even lower altitudes (<20 m), and three are built on the Antarctic continent with very high altitudes (>1500 m). The location of the

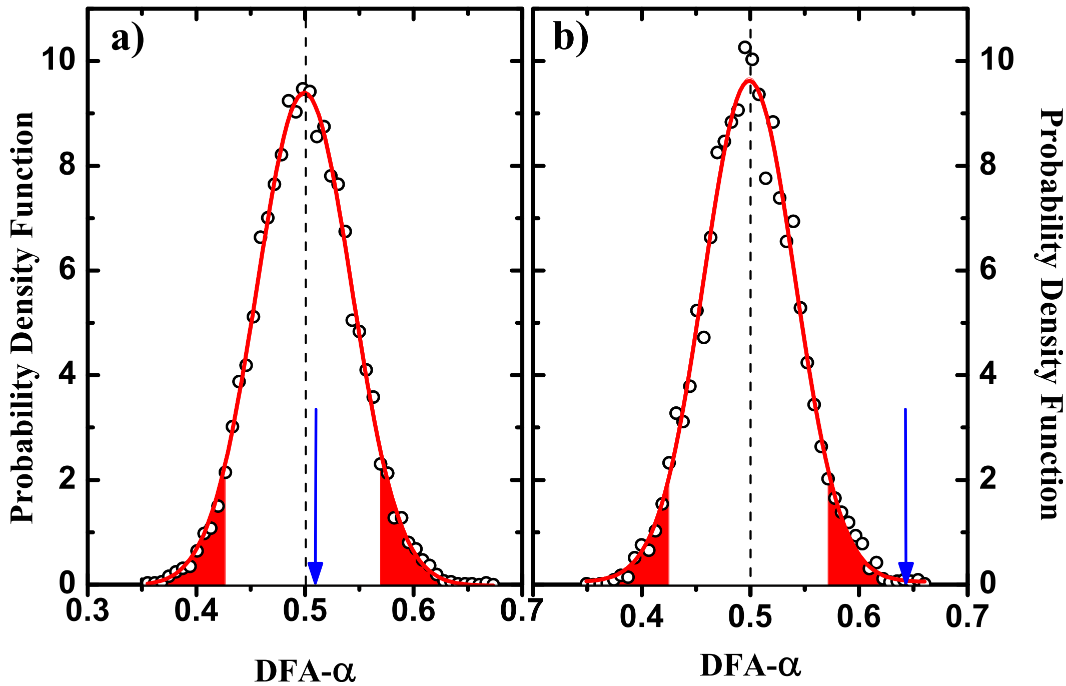

FIG. 4. Uncertainties in DFA-2 analysis, based on the temperature anomalies over (a) the South Pole and (b) Mirny station. In each calculation, we shuffled the temperature anomalies randomly and obtained 10 000 surrogated data without LTM. Theoretically, α calculated from the surrogated data should be 0.5, but after applying DFA-2 the probability density function of α has still a broad shape. The red-tailed regions are determined according to the 2.5% (97.5%) probability threshold, which means that only when the calculated DFA-2 exponent α falls into these regions [as in the case in (b); see the blue arrow] can one believe that the analyzed time series are significantly different from white noise.

last station, Novolazarevskaya (70.8°S, 11.8°E), is relatively special. It is located near the ocean, but not directly at the coastline; it is built on the continent with relatively high altitude (119m), but not as high as the other three continental stations. According to Parish and Bromwich (1987), the station is actually located in a region where strong terrain-induced winds blow from the interior Antarctic to the coast. Other forces that shape the near-surface wind field such as the large-scale pressure gradients associated with cyclonic storms may be only of secondary importance. Therefore, climate in Novolazarevskaya may have continental characteristics. In this way, the 12 stations are classified into three groups: coastline stations (CS), island stations (IS), and Antarctic continental stations (ACS), as shown in Table 1. Although there are few stations in our study, they have a good spatial distribution covering different regions of Antarctica (Fig. 2). Therefore, detailed information as to whether there is LTM over Antarctic can be expected.

To detect LTM, DFA-2 is applied to these 12 temperature records. Considering the possible biases and uncertainties in the results provided by DFA-2, to ensure the accuracy of our detection we also performed a Monte Carlo significance test. As shown in Fig. 4, we take the temperature records over the South Pole (ACS) and Mirny (CS) as examples. From the DFA-2 results (see Figs. 5a,b), one can see that the α values from both temperature records are larger than 0.5. For temperatures over the South Pole $\alpha = 0.51$, while for temperatures over Mirny $\alpha = 0.64$. However, it is difficult to say whether the calculated α is significantly higher than 0.5 or, in other words, whether the considered temperature records are significantly long-term autocorrelated, especially for the case of the South Pole. Therefore, to assess the statistical uncertainty of DFA-2, we shuffled the temperature records over each station for 10 000 times to obtain surrogated data. By shuffling, the temporal correlations are destroyed and LTM removed in the surrogate data. Therefore, theoretically, the DFA exponent α calculated from the surrogated data should be 0.5. However, because of statistical uncertainties and even possible influences from unknown nonlinear trends, wide distributions still arose in our calculations (Fig. 4). Slight differences can be found from the two probability density distributions (Figs. 4a,b) since the surrogated data are generated separately from each temperature records. But the widths of the distributions are roughly the same due to their similar length (South Pole: 57 yr;

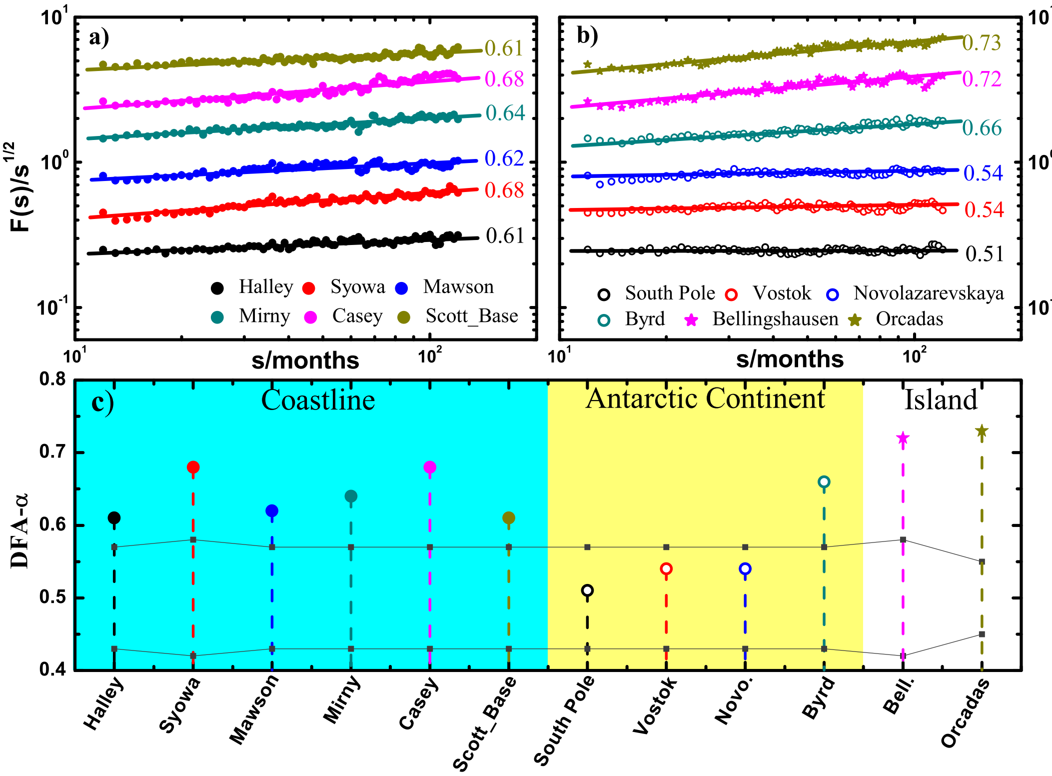

FIG. 5. (a),(b) DFA-2 results of the 12 monthly records and (c) the corresponding Monte Carlo significance test. DFA-2 results are shown from coastline stations (CS) in (a), where one can see all the temperatures are characterized by significant LTM with Hurst exponent $\alpha > 0.6$, and from island stations (IS, the upper two curves) and Antarctic continental stations (ACS, the bottom four curves) in (b). The temperatures from IS are characterized by even stronger LTM, while three out of four continental stations only take on very weak LTM [not significant, see (c)]. Among the continental stations, the temperature over Byrd seems to be an exception with significant LTM. The uncertainty intervals of 95% probability (the two solid lines) from a Monte Carlo significance test are shown in (c). For each station, we shuffled the record for 10 000 times and applied DFA-2 to the surrogated data (with LTM removed). The α values measured from (a) and (b) are marked in (c) as solid circles (coastline), open circles (continent), and stars (island) with different colors.

Mirny: 58 yr). The red-tailed regions are determined according to the 2.5% (97.5%) probability threshold, which means only when the calculated DFA-2 exponent α falls into these regions, we can state that the analyzed time series are significantly different from white noise with a confidence interval of 95%. From Fig. 4, one can see clearly that the temperature from Mirny is significantly long-term correlated (see the blue arrow), whereas for the case of the South Pole there is no remarkable LTM property. It is worth noting that our result over the South Pole is different from the result provided by Franzke (2010), where he found significant LTM in the temperature records over the South Pole. This inconsistency may arise from different analytical methods. As mentioned before, the method based on spectral density analysis may bring us biased estimation. Besides the different methods, the differences in data length could also be responsible for the inconsistence. In Franzke (2010), the surface air temperature record over the South Pole ranges from 1957 to 2000, whereas in our study the time series is extended to 2013. Therefore, it is not surprising to get different results since different methods are applied to data with different lengths.

In Fig. 5, we show the results for all the 12 stations. Figure 5a shows the DFA-2 results of the temperature records from the coastline stations, while Fig. 5b shows the DFA-2 results from the island stations and Antarctic continental stations. Through a Monte Carlo significance test, uncertainty intervals of 95% probability are provided in Fig. 5c. One can see that the interval threshold values are variable among different stations; as mentioned above, this is due to the different data lengths. An example is the case over Orcadas, where we have the longest temperature record (98 yr); the statistics are thus the best with the narrowest uncertainty interval. Note that the DFA exponent α is fitted on the time scale of 1 yr to 10 yr.

It is easy to see that temperatures from CS are all characterized by significant LTM, with $\alpha > 0.6$. For the temperatures from IS (the upper two curves in Fig. 5b), the measured LTM is stronger with $\alpha > 0.7$. But for the temperatures over the Antarctic continent (Fig. 5b, bottom four curves), very weak LTM is measured for the temperature records over the stations of the South Pole, Vostok, and Novolazarevskaya. From the Monte Carlo significance test (Fig. 5c), we cannot reject the hypothesis that the temperatures behave as white noise. According to the results from the above 11 stations, our classification seems to be reasonable in distinguishing stations with different LTM. However, the Byrd station is an exception. Although it belongs to ACS with high altitude, the temperature record still exhibits significant LTM (Figs. 3 and 5b,c). Why do the temperatures over Byrd behave differently from other Antarctic continental stations? Is it because of the reconstruction techniques which may have influenced the temporal characteristics of the record? Or it is just a reflection of the different climatic environments between the West (where Byrd station is located) and East Antarctica? Furthermore, why the temperatures over different regions of Antarctic behave differently, as shown in Fig. 5c? To answer these questions, theories on the origin of climate memory are needed, which unfortunately have not been well established. In the next section, we will provide a detailed discussion of this issue.

4. Discussion

a. *Understanding the different LTM behaviors over Antarctica*

Recently, it has been proposed that one possible origin of climate memory may come from the slow-varying effects of the ocean, where the huge heat storage capacity is thought to be the key factor (Monetti et al. 2003; Yuan et al. 2013). One can consider the mechanism from the perspective of stochastic climate processes (Hasselmann 1976; Yuan et al. 2013). That is, the climate regimes are triggered by small time-scale excitations (or forcing) to begin to change, but slower response subsystems, such as the ocean, usually "remember" the forcing first, and then release the influence slowly on a larger time scale, which further result in the so-called climate memory. This view is supported by many former studies. Particularly, it has been found that temperatures over the oceans normally have the strongest LTM properties (with DFA exponent $\alpha > 0.8$), while over coastal regions the detected LTM become slightly weaker (with DFA exponent $\alpha \sim 0.65$). Over the inner continent, the LTM properties are found to be the weakest, sometimes even close to white noise (with DFA exponent $\alpha \sim 0.5$) (Fraedrich and Blender 2003; Blender and Fraedrich 2003; Eichner et al. 2003). However, what needs to be emphasized is that the large heat capacity of ocean discussed here can only be considered as one possible factor. In fact, following the mechanism above, it should be the interactions among multiscale subsystems that determine the existence of climate memory. As reported in Caballero et al. (2002), by simply combining several AR1 processes with different correlation scales, one could reproduce the scaling behavior measured in observational data. This means all the interrelated factors of different time scales should be responsible, although the effect from ocean may be the dominant one. Therefore, simply from the interactions between our considered region and the ocean, one may make a beforehand guess of whether the temperatures over this region are characterized by climate memory. Although there are still debates on whether this kind of climate memory is long-term or short-term, as in the results shown in Caballero et al. (2002) and the discussion made by Maraun et al. (2004), one needs the record of interest to be long enough to check whether the scaling behavior provided by DFA is indeed due to LTM or only a temporary behavior of short-term memory, and the climatic time series at present is unfortunately not long enough. It is impossible to make a mathematically rigorous test. Thus, as many previous studies did, we normally only focus on a certain time span and define LTM according to the widest scaling range. Although mathematically not rigorous, this treatment will not affect our further research, as long as the research is limited to the given time span.

Recall the results reported by Rybski et al. (2008), where significant LTM is found for the model simulated 2-m temperatures over West Antarctica but not found over East Antarctica; we prefer to understand the "abnormal" behavior at the Byrd station by using the theory introduced above—that is, to check whether there are close interactions between the West Antarctica (where the Byrd station is located) and external slow-varying systems (ocean). In fact, it has been reported that West Antarctica is a key region for heat and moisture transport (Cullather et al. 1998). Influenced by ocean variations from both far away tropical Pacific/Atlantic water (Ding et al. 2011; Li et al. 2014) and nearby clockwise propagated eddies, we argue that the seemingly abnormal behavior at the Byrd station is not unexpected. Furthermore, because of the Transantarctic Mountains, the influences are limited to West Antarctica. Thus, these mountains form a clear border line between West and East Antarctica (Nicolas and Bromwich 2014). In East Antarctica, however, the continent is only weakly influenced by the ocean. As a result, temperatures over this region have high probabilities to behave as white

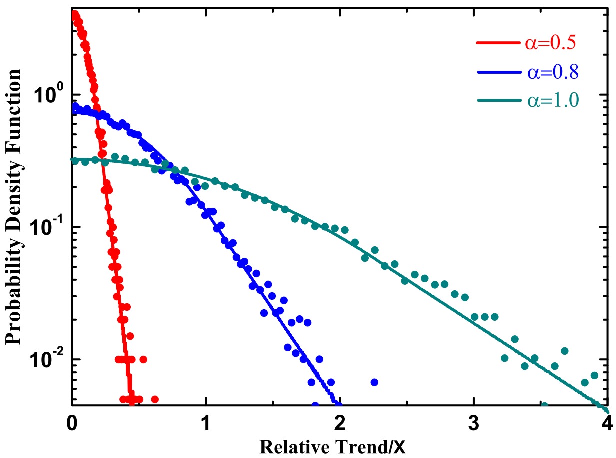

FIG. 6. Trend distribution of time series with equal length ($L = 1000$), but different LTM ($\alpha = 0.5$, red; $\alpha = 0.8$, blue; and $\alpha = 1.0$, dark cyan). The solid circles are the numerical results estimated from artificially generated time series (10 000 samples for each α), while the lines are the results calculated from the formulas derived by Lennartz and Bunde (2011). For time series without LTM ($\alpha = 0.5$), narrow width is found, which may be mainly due to statistical errors. While for time series with LTM ($\alpha > 0.5$), wider distribution is found. The stronger LTM is, the wider a distribution is found. The lines fit the numerical results very well.

noise. As shown in Fig. 5c, indeed no significant LTM has been measured in the temperatures over the South Pole, Vostok, and Novolazarevskaya. Therefore, the different LTM behaviors between temperature for the Byrd station and that over other continental stations could be explained as a reflection of the different climatic environments between West and East Antarctica. Furthermore, as for the stations from coastline and from islands, it is obviously not surprising to find significant LTM in temperature, since these stations are all located in regions where close interactions with the ocean can be found.

b. *Effect of LTM on trend evaluation*

Considering that LTM is a relatively new concept that has not been widely used in trend evaluation, to make our study (detection of LTM in temperatures over Antarctica) more valuable, we would like to further emphasize the importance of LTM by extending our discussion briefly to the trend significance analysis. We first start from the analysis of artificial data. Figure 6 shows the distribution of the trends estimated from three kinds of artificial time series with equal length ($L = 1000$), but different LTM ($\alpha = 0.5$, $\alpha = 0.8$, and $\alpha = 1.0$). The trends calculated here actually are relative trends x, defined as $x = \Delta/\sigma_t$, where Δ is the total observed temperature increase measured by linear regression, and σ_t is the standard deviation around the regression line (Lennartz and Bunde 2011). From 10 000 samples, we obtain the probability density function of relative trend x for each kind of artificial time series (solid circles with different colors). It is clear that for time series without LTM ($\alpha = 0.5$), only narrow trend distribution is found owing to statistical errors, whereas for time series with LTM ($\alpha = 0.8$, $\alpha = 1.0$) much wider distributions appear. When studying observed time series, only if the trend falls in the tail region, or in other words, exceeds the confidence interval $[-x_Q, x_Q]$ of a given confidence probability Q, can one say that the observed trend is significant. Obviously, from Fig. 6, time series with LTM have much wider confidence intervals. To get x_Q, one straightforward way is to make a numerical test by applying a Monte Carlo simulation and study artificial time series with the same length L, the same LTM strength α, and also the same distribution, as we did in Fig. 6. But this requires lots of computing time. To make the evaluation simpler, Lennartz and Bunde (2011) recently developed a new scaling approach with theoretical formulas derived. These formulas can be used to simulate the probability density function of relative trend x, as shown in Fig. 6 (the lines with different colors, which fit very well with the solid circles), and further provide an estimation of the confidence interval $[-x_Q, x_Q]$ under a given confidence probability Q. Below is the formula for calculating x_Q:

$$x_Q(\alpha, L) = \alpha^{\delta_L} C_L \left\{ \frac{w_L^2}{2} + \ln\left(\frac{2}{1-Q}\right) - \ln[\mathrm{erf}(w_L/\sqrt{2})(\sqrt{2\pi}w_L) + 2e^{-w_L^2/2}] \right\}, \quad (3)$$

where $C_L \approx C^{(0)} + C^{(1)}\ln(L)$, $C^{(0)} \approx 2.04$, $C^{(1)} \approx -0.2$, $\delta_L \approx \delta^{(0)} + \delta^{(1)}\ln(L)$, $\delta^{(0)} \approx -0.57$, $\delta^{(1)} \approx 0.61$, $w_L^2 \approx w^{(0)} + w^{(1)}\ln(L)$, $w^{(0)} \approx -6.32$, and $w^{(1)} \approx 1.41$. Also, L is the length of the record, α is the DFA-2 exponent, Q is the confidence probability, and erf(z) is the error function. With this formula, we can get the confidence interval x_Q by simply inputting the data length L, the DFA-2 exponent α, and the confidence probability Q. If the observed relative trend x exceeds the interval $[-x_Q, x_Q]$, a significant trend can be detected. Conversely, if we input the observed relative trend x, data length L, and the DFA-2 exponent α into Eq. (3), the trend significance $S(Q)$ could also be derived from Eq. (3). Although the formulas are derived by studying Gaussian distributed records, it has been discussed that they are applicable not only for Gaussian distributed time series, but also for time series with non-Gaussian distribution, as long as they do not exhibit fat tails (Lennartz and Bunde 2011). Therefore, we can apply them to the temperature records over Antarctica. For more details of this method, we refer to Lennartz and Bunde (2011).

TABLE 2. Trend evaluation of the 12 monthly records over Antarctica. Data length L, temperature increase Δ, standard deviation σ_t around the trend line, relative trend x, and the DFA-2 exponent α are listed in the table. To evaluate the trend, we show both the confidence interval x_Q ($Q = 0.95$) and the significance level S. Besides the results with LTM taken into account ($x_{0.95}^{\mathrm{LTM}}$, S^{LTM}), evaluations from conventional methods based on the assumption of AR1 processes and white noise are also listed in the table, as $x_{0.95}^{\mathrm{AR}}$, S^{AR}, $x_{0.95}^{W}$, and S^{W}. A significance level S larger than 95% is marked by one asterisk (*) and S larger than 99% is marked by two (**).

Station	L	Δ(°C)	σ_t	x	α	$x_{0.95}^{\mathrm{LTM}}$	S^{LTM}	$x_{0.95}^{\mathrm{AR}}$	S^{AR}	$x_{0.95}^{W}$	S^{W}
Halley	684	−0.51	2.65	−0.19	0.61	±0.50	52.2%	±0.29	80.7%	±0.26	85.0%
Syowa	564	−0.10	1.85	−0.05	0.68	±0.77	≈ 0	±0.37	22.6%	±0.29	28.7%
Mawson	708	−0.14	1.94	−0.07	0.62	±0.52	≈ 0	±0.29	38.3%	±0.26	43.4%
Mirny	691	0.37	2.00	0.19	0.64	±0.58	39.3%	±0.30	77.8%	±0.26	84.2%
Casey	648	0.32	2.13	0.15	0.68	±0.74	10.5%	±0.33	63.6%	±0.27	73.5%
Scott Base	610	0.87	2.68	0.33	0.61	±0.52	80.5%	±0.32	95.1%*	±0.28	98.0%*
Bellingshausen	540	0.78	1.61	0.48	0.72	±0.95	71.5%	±0.45	96.3%*	±0.29	99.9%**
Orcadas	1176	1.90	2.25	0.84	0.73	±0.76	96.8%*	±0.30	99.9%**	±0.20	99.9%**
South Pole	684	0.17	2.44	0.07	0.51	±0.27	24.3%	±0.28	37.1%	±0.26	40.1%
Vostok	616	0.70	2.43	0.29	0.54	±0.35	90.8%	±0.33	91.2%	±0.27	96.1%*
Novolazarevskaya	623	0.79	1.78	0.45	0.54	±0.34	98.3%*	±0.32	99.3%**	±0.27	99.9%**
Byrd	684	2.02	3.08	0.65	0.66	±0.65	95.1%*	±0.31	99.9%**	±0.26	99.9%**

In Table 2, we show the confidence interval $[-x_{0.95}, x_{0.95}]$ and the trend significance S of the temperatures over all the 12 stations. Besides the results calculated from Eq. (3), results from conventional methods based on the assumption of AR1 process and even white noise (Santer et al. 2000; Tamazian et al. 2015) are also presented in Table 2. One can see that after taking LTM into account, the trend evaluation becomes more rigorous, especially for the ones with stronger LTM. For instance, in the Bellingshausen station, if we assume the temperature records as white noise, then the 0.78°C temperature increase from 1969 to 2013 is significant with $S > 99\%$. If we assume the temperature records as AR1 processes, then the temperature increase is significant with S larger than 95%, but smaller than 99%. However, if we take the strong LTM ($\alpha = 0.72$) into account, the temperature increase is not significant ($S = 71.5\%$). By using Eq. (3), we find that only 3 (out of 12) stations have shown significant warming trends. If we assume the temperature records show AR1 processes (white noise), 5 out of 12 (6 out of 12) stations will be picked out. Since trend evaluation is not our main focal point, we do not include a detailed discussion on the reasons why different stations have different trend significance. But from the results shown in Table 2, one can find that 1) the temperatures over most Antarctic stations do not show any significant trends, even for the AR1 or white noise null models, which is in line with the studies by Turner et al. (2005); and 2) LTM indeed is a factor that can affect the estimation of trend significance. If a time series is characterized by LTM, we cannot simply assume it as AR1 processes or white noise. In the end, we need to note that a trend with $S < 95\%$ does not need to be of pure natural origin, while a trend with $S > 95\%$ does not need to be totally "anthropogenic" either. The trend significance S is actually a measurement that can be used to quantify the probability of an observed trend being affected by external factors. Obviously, from our results, this probability is not high for most of the Antarctic stations.

5. Conclusions

In this study, surface air temperature records of 12 stations from different regions of Antarctica are analyzed by means of DFA. After the Monte Carlo significance test, different LTM behaviors are found. Temperatures observed from coastlines and temperatures observed from islands are all characterized by significant LTM, while temperatures records observed from continental stations behave differently. In East Antarctica, continental temperatures from the South Pole, Vostok, and Novolazarevskayz behave closer to white noise, whereas in West Antarctica significant LTM is found in the Byrd station. These different results may be explained by studying the interactions between local weather system and external slow-varying systems (ocean); therefore, we argue that the difference can be considered as a reflection of the different climatic environments between the West and East Antarctica. Since according to the discussion above (Fig. 6 and Table 2) the existence of LTM can increase the uncertainty of trend evaluation, when studying the warming trend over Antarctica special attention should be paid to the coastline, islands, and West Antarctica, where significant LTM is detected in this study.

After submitting this work, we learned of a closely related study by Ludescher et al. (2015) in which, by using DFA-2, similar exponents for the Antarctic records (not exactly the same 12 stations as we use) have been obtained. Their trend analysis shows that only 1 station (out of 13) has a significant warming trend ($S > 95\%$) if the

LTM is taken into account, whereas 4 (out of 13) stations will be picked out with significant warming trend if AR1 processes are assumed. The results are in line with ours and therefore emphasize the importance of LTM in trend evaluation.

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