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The impact of inter-annual variability of annual cycle on long-term persistence of surface air temperature in long historical records

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Abstract Previous studies in the literature show that the annual cycle of surface air temperature (SAT) is changing in both amplitude and phase, and the SAT departures from the annual cycle are long-term correlated. However, the classical definition of temperature anomalies is based on the assumption that the annual cycle is constant, which contradicts the fact of changing annual cycle. How to quantify the impact of the changing annual cycle on the long-term correlation of temperature anomaly variability still remains open. In this paper, a recently developed data adaptive analysis tool, the nonlinear mode decomposition (NMD), is used to extract and remove time-varying annual cycle to reach the new defined temperature anomalies in which time-dependent amplitude of annual cycle has been considered. By means of detrended fluctuation analysis, the impact induced by inter-annual variability from the time-dependent amplitude of annual cycle has been quantified on the estimation of long-term correlation of long historical temperature anomalies in Europe. The results show that the classical climatology annual cycle is supposed to lack inter-annual fluctuation which will lead to a maximum artificial deviation centering around 600 days. This maximum artificial deviation is crucial to defining the scaling range and estimating the long-term persistence exponent accurately. Selecting different scaling range could lead to an overestimation or underestimation of the long-term persistence exponent. By using NMD method to extract the inter-annual fluctuations of annual cycle, this artificial crossover can be weakened to extend a wider scaling range with fewer uncertainties.

Keywords Annual cycle · Long-term correlation · Temperature anomalies · Nonlinear mode decomposition (NMD) · Time-dependent amplitude

1 Introduction

It has been recognized that climate system usually exhibits its memory or persistence related to different regimes. For instance weather is short-range persistent and typically breaks on 1 week, a time period that corresponds to the average duration of "general weather regimes" (Eichner et al. 2003). Moreover, on monthly or longer time scales, the presence of memory is believed to be originated from the slow response to external forcing such as solar irradiance and sea surface temperature. Long-term memory (LTM) in climate system will severely affect the estimates of climate statistics, such as the significance of estimated trends (Franzke 2012, 2013), confidence interval of time averages (Massah and Kantz 2016) and can help distinguish whether changes of climate statistics are the results of internal variability or external forcing (Lennartz and Bunde 2009; Bunde et al. 2014; Ludescher et al. 2016). Therefore understanding climate memory is of great importance for the analysis of the whole climate system. Since the behaviors on longer time scales are governed by complex coupled processes in nature, LTM in climate process is hard to estimate. In recent years, the detrended fluctuation analysis (DFA) method has been established (Peng et al. 1994) as an essential tool for the quantification of LTM. By using DFA, researches on various meteorological records ranging from air temperature (Koscielny-Bunde et al. 1996,

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1998; Talkner and Weber 2000; Monetti et al. 2003; Eichner et al. 2003; Kurnaz 2004a, b; Yuan et al. 2010; Franzke 2010), relative humidity (Chen et al. 2007; Lin et al. 2007) to wind field (Govindan and Kantz 2004; Li et al. 2014), total ozone anomalies (Varotsos and Kirk-Davidoff 2006; Vyushin et al. 2007), etc., indicate that the presence of LTM is ubiquitous in climate.

Compared with traditional auto-correlation analysis or the power spectrum density analysis, DFA method can better quantify the scaling behavior of time series by systematically removing trend effect (Kantelhardt et al. 2001; Hu et al. 2001). Trends contain low-frequency changes, for example, linear trend generated by the global warming and the oscillations induced by annual cycle. These trends may bring out spurious correlation so that even uncorrelated data appears correlated. Although the DFA method can remove part of the trend effect, it cannot remove the influences of slowly changing oscillations spontaneously (Kantelhardt et al. 2001; Hu et al. 2001). Therefore, to calculate the long-term correlation, the most prominent climate oscillation—annual cycle (AC) should be removed first by other ways.

Traditionally, we subtract the annual cycle by $T_i - \langle T_i \rangle$, where T_i is original records and $\langle T_i \rangle$ is a long-time climatological average for each calendar day of every year, which is called climatology annual cycle (CAC). CAC has been taken to eliminate the slowly changing oscillation impact nearly in all related long-term correlation quantification (Koscielny-Bunde et al. 1996, 1998; Talkner and Weber 2000; Monetti et al. 2003; Eichner et al. 2003; Govindan and Kantz 2004; Kurnaz 2004a, b; Varotsos and Kirk-Davidoff 2006; Chen et al. 2007; Lin et al. 2007; Vyushin et al. 2007; Yuan et al. 2010, 2015; Yuan and Fu 2014; Li et al. 2014). Actually, annual cycle defined through this way heavily rely on an implicit assumption that annual cycle is an exact repeat of itself year after year. However, despite the external solar forcing, which is almost constant at decadal scale, there is no guarantee that the annual cycle has to be same every year under a changing climate. Ever since last century, changes in annual cycle have been reported in many studies (Thomson 1995; Wallace and Osborn 2002; Jones et al. 2003; Barbosa 2009; Stine et al. 2009; Vecchio and Carbone 2010; Qian et al. 2011a, b; Qian and Zhang 2015; Bye et al. 2013). Fluctuations in amplitude and phase of annual cycle may be caused by the nonlinear response to external forcing such as sea ice boundary (Eliseev and Mokhov 2003), increased CO2 (Mann and Park 1996; Thomson 1997), earth's precession (Thomson 1995; Vecchio et al. 2010) and anthropogenic influences (Qian and Zhang 2015). In addition, internal variability like atmospheric circulation (Stine and Huybers 2012) can also explain some changes of annual cycle. The fact of changing annual cycle contradicts the assumption applied in CAC definition and has been challenged in recent studies suggesting redefinition of climate anomalies (Wu et al. 2008; Qian et al. 2011a, b). Changes in the amplitude of the annual cycle can affect the estimation of climate trends and variability (Qian et al. 2011a), for example, the classification of El Niño/La Niña years (Qian et al. 2011b). Will this cause serious problem in estimating the long-range correlation by means of DFA? How can this changing annual cycle affect the quantification of long-range correlation of large-scale anomaly variability? If CAC indeed results in problem in correctly estimating the long-range correlation of large-scale anomaly variability, can we weaken or totally eliminate this impact? These questions will be answered in this paper.

Since the annual cycle is changing, when applying DFA to calculate LTM, only subtracting the constant CAC can bias the correct estimation of LTM, how to extract the changing annual cycle is crucial to a correct estimation of LTM. Owing to the lack of a unique and precise definition of annual cycle, the extraction of a time-varying annual cycle from a climate time series suffers big challenges. Previous studies have used Fourier analysis (Mokhov 1985), sinusoidal model fitting and complex demodulation (Paluš et al. 2005), autoregressive process (Barbosa 2009), empirical mode decomposition (EMD, Vecchio et al. 2010; Capparelli et al. 2011) and ensemble empirical mode decomposition (EEMD, Wu et al. 2008; Qian et al. 2011a, b) to analysis the time-varying annual cycle. In this paper, we applied a new developed statistic method named nonlinear mode decomposition (NMD, Iatsenko et al. 2015) to extract the changing annual cycle of daily mean temperature from seven stations in Europe with a long period and analyzed their LTM using DFA. The DFA results for temperature anomalies defined through CAC and NMD will be compared. The changing annual cycle can be easily found in the monthly mean air temperature series, see Fig. 1, where the time-dependent amplitude of annual cycle is dominated. This indicates that the inter-annual variability induced from changing amplitude of annual cycle is not a negligible issue in the estimation of LTM. For simplicity, the analysis in this paper will focus on the changing amplitude of annual cycle only.

The paper is organized as follows. A short introduction to the data sets used in this paper and the analysis methods will be given in Sect. 2. The results are presented in Sect. 3. In Sect. 4, a summary with further discussion is made.

2 Data and method

2.1 Data

The seven daily long historical SAT records are downloaded from the Royal Netherlands Meteorological Institute (KNMI) Climate Explorer (http://climexp.knmi.nl/), the

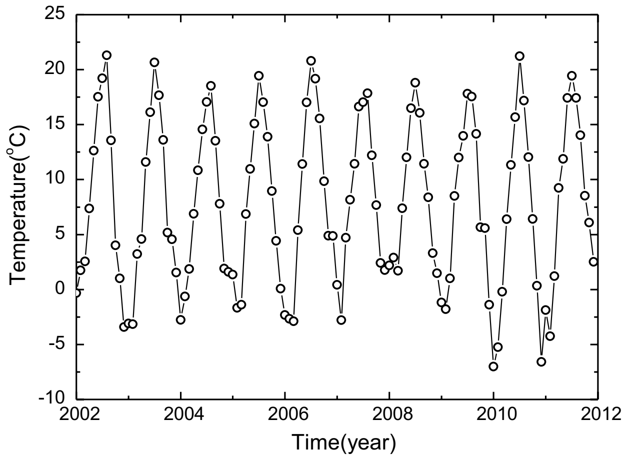

Fig. 1 Changing annual cycles exemplified by a segment of monthly mean SAT series at Stockholm

detailed information related to these seven records is shown in Table 1. We choose these records for they are among the longest ones (longer than 150 years) with few missing points. Only the records from Milan have few missing points during the period 2001–2007 and they are completed by nearest interpolation. In order to eliminate the effect of short-term memory from weather regimes, after removing annual cycle, we average the daily anomaly data over 2-week non-overlapping windows to reach bi-weekly mean anomaly series.

2.2 Method

2.2.1 Definition of temperature annual cycle and anomalies

We use a new data adaptive decomposition tool named Nonlinear Mode Decomposition (NMD) to extract changing annual cycle of daily mean SAT. It decomposes a given signal into a set of physically meaningful oscillations with any wave form in the frequency space, based on the combination of time–frequency analysis techniques and surrogate data tests (Schreiber and Schmitz 2000), and simultaneously removes the noise. We will give a short description about its procedure, the details can be found in Iatsenko and his coauthors' works (Iatsenko et al. 2015):

(a) Extract the fundamental harmonic of a Nonlinear Mode (NM) accurately from the signal's time–frequency representation.
(b) Find candidates for all its possible harmonics, based on its properties.
(c) Identify the true harmonics among them using surrogate data sets' tests.
(d) Reconstruct the full NM by summing together all the true harmonics; subtract it from the signal, and iterate the procedure on the residual until a preset stopping criterion is met.

When applying NMD to daily temperature records, at least one NM will be extracted. The first/fundamental harmonic of NM has a period of 365 days (12 months), and the NM may contain multiplier harmonics with periods of 6, 4, 3, and 2.4 months. Whether those harmonics will be extracted or not is determined by the surrogate test. That NM is considered to be the "annual cycle". The NMs based on other fundamental frequency would not be included whether they have been extracted or not. Subtracting NM annual cycle (NMAC), the residual is defined as anomaly. An example of the NMD of daily mean temperature is presented in Fig. 2. Since the NMD method can remove mean value and linear trend of the data automatically, the mean value and linear trend have been removed from the observation records first before we carry out CAC and comparison analysis in this paper. As we can see from Fig. 2a, the NMAC fits observations quite well. Besides, the time evolution of each harmonics in NMAC (Fig. 2b) and their frequency, amplitude and phase can be obtained through NMD.

2.2.2 Analysis of long-term correlation of SAT anomalies

To measure the LTM of SAT records, detrended fluctuation analysis (DFA) is applied to the two kinds of anomaly $T_i(s)\,(i = 1, 2, 3, \ldots, N)$ which are the deviations from its annual cycle, CAC and NMAC, respectively. DFA method,

Table 1 Details of the SAT data used in this paper

Station	Country	Location	Time span	Length (year)
Bologna (B)	Italy	44.5N, 11.35E	1814–2011	198
Hohenpeissenburg (H)	Germany	47.8N, 11.01E	1814–2011	198
Milan (M)	Italy	45.47N, 9.19E	1763–2007	245
Prague (P)	Czech Republic	50.09N, 14.41E	1775–2004	230
Stockholm (S)	Sweden	59.31N, 18.07E	1756–2011	256
Vienna (V)	Austria	48.23 N, 16.35E	1856–2011	156
Zagreb (Z)	Croatia	45.82N, 15.98E	1862–2011	150

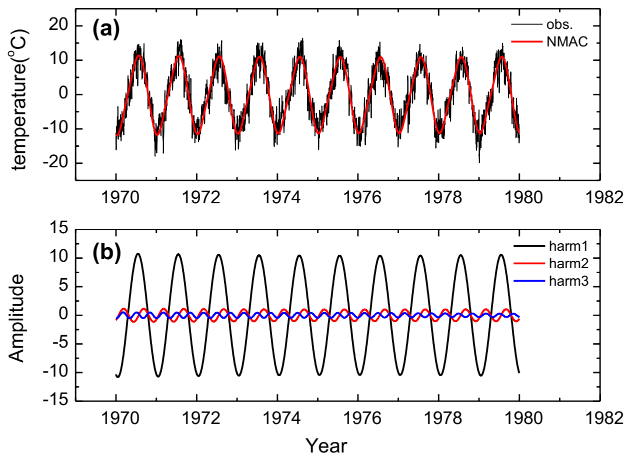

Fig. 2 Piece of NMD series at Bologna: **a** the comparison of detrended SAT records and its NMAC; **b** three extracted physically meaningful harmonics in the NMAC

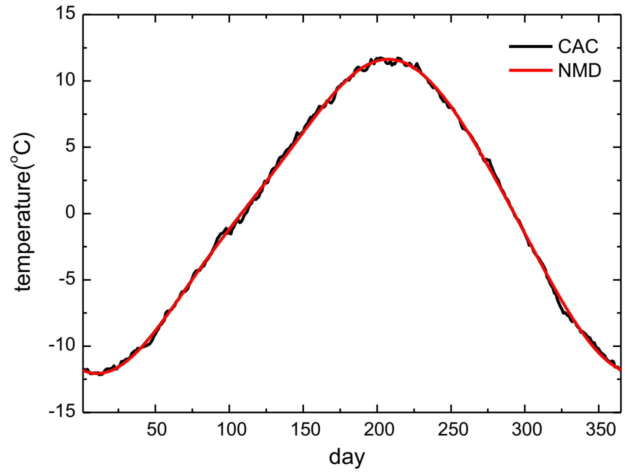

Fig. 3 The comparison between CAC (*black*) and averaged NMAC (*red*) at Bologna

first developed by Peng et al. (1994), is efficient to distinguish trends from long-range fluctuations which are intrinsic. The algorithm is as follows.

For anomaly T_i, we first calculate the profile of the time series as

$$Y_k = \sum_{i=1}^{k} T_i \,(k = 1, 2, 3, \ldots, N)$$

where N is the length of the record. Then the profile series is divided into N_s non-overlapping segments of equal length s with $N_s = [N/S]$. Since the length of the series is not always exactly a multiple of s, a short part of data will remain at the end of series. The same procedure is repeated for the reverse record to include the remaining part. Therefore we get $2N_s$ segments. In each segment, the local trend calculated by a polynomial fit is subtracted and the variance of it refers to the corresponding square fluctuation $F_s^2(k)$. Then the root-mean-square fluctuations $F(s)$ is obtained by averaging over all segments of size s,

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

For the case of long-range power law correlations, $F(s)$ will increase as a power law

$$F(s) \sim s^{\alpha}$$

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

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

the exponent α and γ are connected as (see Talkner and Weber 2000)

$$\gamma = 2(1 - \alpha).$$

For uncorrelated data, $\alpha = 0.5$, while long-term memory processes are characterized by $1 > \alpha > 0.5$, $\alpha < 0.5$ indicates anti-persistence. It is worth noting that there are different orders of DFA corresponding to the orders of polynomial fit. DFAn can eliminate trends of order n in the profile and n-1 in the original time series (Kantelhardt et al. 2001). In this article we applied DFA2.

3 Results

3.1 The inter-annual variation of annual cycle

Take Bologna as an example, we compare the annual cycle extracted by NMD which is so called NMAC to the detrended temperature records and its climatological annual cycle (CAC) in Figs. 3 and 4. It is well known that CAC is calculated by averaging each calendar day of the year in a long time span so that it actually only presents the mean state of the annual cycle. Following this way we calculated the mean state of NMAC and compared it to CAC (Fig. 3). They nearly overlap together and show little differences which means NMAC is reliable in the aspect of depicting mean state of annual cycle.

Furthermore, the details of changing NMAC (red line) in different time periods are given in Fig. 4 comparing with the observation (black line) and CAC (blue line). Limited by the length of the data, we only show some pieces from the whole series. Since the scale of coordinates has been unified, it is clear that the amplitude in the top subfigure is larger than the bottom one. The NMAC capture these features successfully whereas CAC cannot reflect the differences between year and year. The CAC underestimate the true annual cycle on the top subfigure (Fig. 4a), but

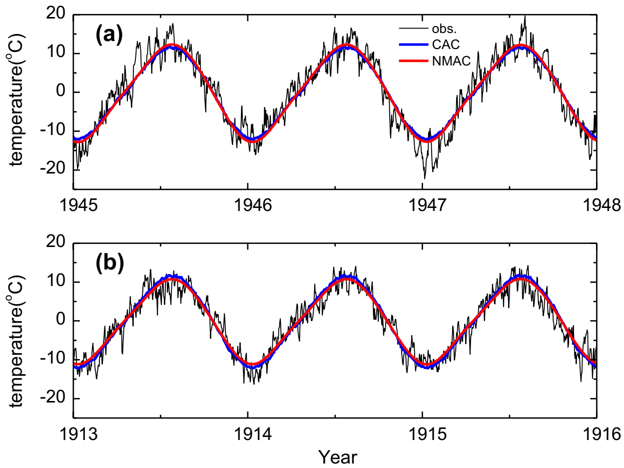

Fig. 4 Comparison between CAC (*red*) and NMAC (*blue*) from pieces of temperature series (*black*) **a** from 1945 to 1948; **b** from 1913 to 1916 at Bologna

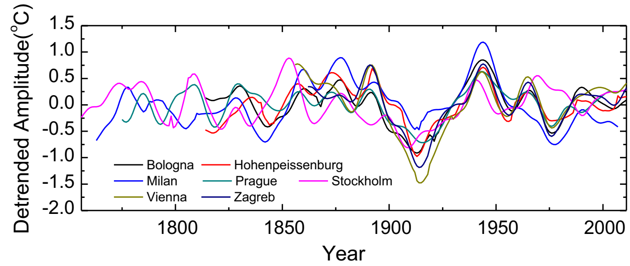

Fig. 5 The changing amplitude extracted by NMD at each station, mean value of each curve has been shifted to zero

overestimate the true annual cycle on the bottom subfigure (Fig. 4b). Over this region, the changing annual cycle mainly results from the changing amplitude not from changing phase. This is the reason why we only consider the changing amplitude of annual cycle in this paper. The changing amplitude of annual cycle extracted by NMD will lead to the inter-annual change of annual cycle, which will alter the estimation for LTM of SAT anomaly variability.

The NMD method is further applied to other 6 stations to extracts their NMACs. Since the NMAC varies continuously with time, we calculate its amplitude each year through (maximum-minimum)/2. Almost all the stations exhibit consistency in their amplitude variation (Fig. 5). To be more precise, they all descend to their lowest around 1920s and then climb to the peak around 1945s. The amplitudes reach another lower value around 1975s, which is coincident with the climatic regime shift of the mid-1970s. It should be pointed out that the evolution amplitude of annual cycle over Milan (much close to Mediterranean Sea) and Stockholm (located close to higher latitude, 59.31N see Table 1) still take some detailed distinctive changing patterns. This is because the temperature of Milan is dominated by the Mediterranean Sea climate and Stockholm is affected by its high latitude location.

Through the above results, the amplitudes of annual cycle are indeed changing with time and show some regional consistence, confirming the results in Qian and Zhang (2015). NMAC is proved to be efficient and reliable in representing this time-varying amplitude of annual cycle while CAC not. When considering the inter-annual variability of annual cycle, what changes will occur in the estimation of long-term memory is demonstrated in the next part.

3.2 Long-term correlation of temperature anomalies

The DFA method is employed to SAT anomalies obtained through CAC and NMAC. Since the properties of LTM in this region have been discussed in previous studies (see Capparelli et al. 2011; Yuan and Fu 2014), we will focus on the differences induced by differently defined AC and anomalies. According to the power law $F(s) \sim s^{\alpha}$, usually we take the logarithm and make a linear fit to calculate the exponent α. Due to the edge effect caused by the method in small scales and the length of records, we fitted the scaling law in the range from 200 days to 20 years. Within this range, the changes in DFA exponent $\alpha$is not significant under 95% confidence level (see Table 2). However the R-squared presents a slight increase in NMD compared to CAC for all the stations, at the same time all standard errors in NMD are smaller than those in CAC. As we fixed the fitting range, R-squared and standard error can reflect the goodness of fit to a certain extent. From this point of view, the results from NMD perform scaling law a little bit better.

Besides, the differences in the DFA curves also suggest that results from NMD are much closer to the straight lines (Fig. 6). Except for Hohenpeissenburg, the DFA curves from two methods showed separation around the 600-day scale (inter-annual scale) in all the stations. Due to the compressing effect caused by double-log coordinates, those differences between two curves seem not clear enough. To further amplify the differences, we rescale the dependent variable $F(s)$ to $F(s)/s^{\alpha}$ so that the slope should be zero within the scaling range. Through this way we can better find the optimal scaling range for the scaling behavior. Since the exponent αdoes not change significantly (all exponents from NMD are slightly larger than those from CAC in the range from 200 days to 20 years), we simply adopt the $\alpha$from NMD method in the transformation (see Fig. 7).

Except for Hohenpeissenburg in which both methods show nearly the same behavior, all results over other stations exhibit marked separation between two methods with

Table 2 DFA exponents and the fitting parameters

Station	Method	DFA exponents	p	Standard error
Bologna	CAC	0.6117	0.9981	0.0070
	NMD	0.6166	0.9996	0.0034
Hohenpeissen-burg	CAC	0.5720	0.9997	0.0025
	NMD	0.5732	0.9998	0.0021
Milan	CAC	0.6184	0.9986	0.0059
	NMD	0.6262	0.9998	0.0024
Prague	CAC	0.6431	0.9996	0.0035
	NMD	0.6453	0.9999	0.0020
Stockholm	CAC	0.6913	0.9983	0.0074
	NMD	0.7008	0.9997	0.0032
Vienna	CAC	0.6187	0.9992	0.0046
	NMD	0.6256	1	0.0010
Zagreb	CAC	0.6130	0.9987	0.0057
	NMD	0.6176	0.9998	0.0023

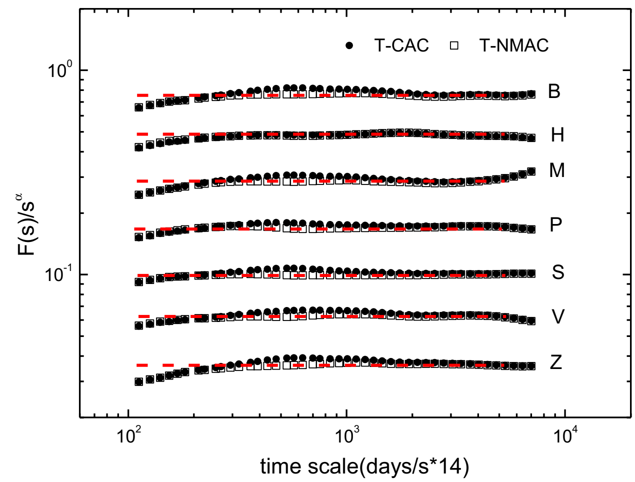

Fig. 7 The scaled fluctuation function v.s. window in DFA, for clarity, each line has been vertically shifted, where *solid dots* for results from CAC filtering, *hollow rectangles* for results from NMAC filtering, and *red dash lines* for eye-guided scaling range

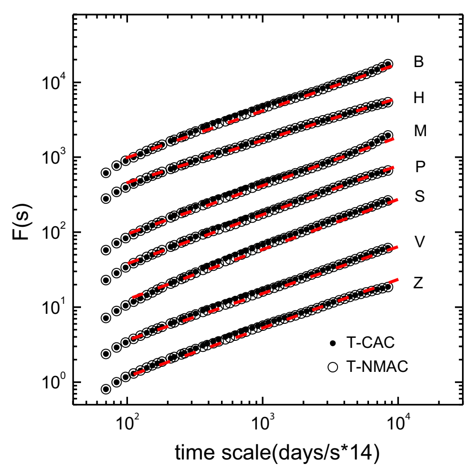

Fig. 6 DFA results for the anomalies defined by CAC and NMD, for clarity, each line has been vertically shifted, where *solid dots* for results from CAC filtering, *hollow circles* for results from NMAC filtering, and *red dash lines* for eye-guided scaling range

all lines from NMD presented straight lines and lines from CAC deviated from the straight lines (see Figs. 6 and 7). These separations span nearly over the whole scaling range used to estimate the exponent α. In this scaling range, the result of CAC appears a crossover with a maximum artificial deviation centering around 600 days (inter-annual scale). The crossover is generally thought to be caused by the short-range correlation or the drawback from DFA method (Peng et al. 1994; Kantelhardt et al. 2001). However in our analysis, the influences of short-range correlation have already been removed by averaging the daily data over 2-week-long windows. Since all crossover points with a maximum artificial deviation centering around 600 days are only found in the CAC related results, they are possibly induced artificially by CAC not correctly removing the annual cycle. It is obvious that there is no inter-annual variability in CAC. This lack may lead to a weak 1-year period oscillation left in anomalies which affects the estimation of LTM. For instance, if the smaller scaling range before this maximum artificial deviation point (e.g. from 1 month to 600 days) is chosen, the slope fitted in this range is actually overestimated. Similarly, if the larger scaling range after this maximum artificial deviation point (e.g. from 600 days to 20 years) is chosen, the exponent would be underestimated. Since the scaling range we selected exactly contains this point, the exponents do not change significantly (Table 2). For a majority of meteorological stations in the world, their records do not last such long as the stations we studied. Thus the scaling range generally was chosen at the early part around 600 days, which will lead to an overrated DFA exponent. To verify our supposal, detailed results from artificially generated time series will be demonstrated next.

3.3 Results from idealized artificially generated time series

Analysis from the observational records suggests a great difference in the estimation of LTM when eliminating different annual cycle. When applying CAC, a crossover in the DFA curves with a maximum artificial deviation around 600 days was observed. Does the crossover really exist or the NMD method underrates the long-term correlation? To answer this question, we carry out an idealized experiment by generating series with known long-term correlation.

We first generate a changing annual cycle by modulating the sinusoidal waves following the real series. Taking the changing annual cycle of Bologna as the reference, the first harmonic dominates the annual cycle and its amplitude exhibits a prominent decrease. Therefore we construct a linear declining amplitude in annual cycle with the rate at 0.046 °C/10 years (same as Bologna) and a constant semi-annual cycle. As for temperature anomalies, a simple Fourier-filtering technique (see Schreiber and Schmitz 2000) is used to generate linear long-term correlated records with known LTM exponent. We set $\alpha = 0.6$ (Table 2) to simulate the temperature anomalies of Bologna. The noise intensity is equal to the standard deviation of anomalies and the length of data is 198 years. The artificial temperature series is generated by summing the modulated annual and semi-annual cycles with a long-term correlated series. The experiment is repeated for 100 times and the results will be presented through mean value of them (see Fig. 8).

As expected, the experiments of artificially generated series reproduce almost the same results found in the observational records. The line from NMD is nearly straight and the line from CAC is deviated from the straight line (Fig. 8a). The separation in DFA curves is observed in a long time range and the result of CAC appears a crossover with a maximum artificial deviation centering around 600 days (Fig. 8a). The blue line from generated correlated series without annual cycle is considered to be theoretical and referential. In order to find the discrepancies from the referential one, the rescaled fluctuations vs. scale is presented (Fig. 8b), the separation at maximum artificial deviation centering around 600 days is even more remarkable. Actually results from both two methods exhibit maximum departure from the theoretical line around 600 days. Result from CAC has a convex crest while result from NMD has a concave trough, but NMD performs much better and weakens this departure greatly since the maximum departure in CAC is nearly four times of this found in NMD.

The relative DFA exponent errors $(\alpha - \alpha_0)/\alpha_0 \times 100\%$, where α_0 denotes the DFA exponent of referential generated series, over the range from the lower limit of 100 days to the different upper limits are calculated. With the gradually increased upper limit, the errors of NMD remain always lower than CAC. The biggest deviation with 9.69% from CAC and 2.36% from NMD is observed around 600 days (Table 3). And the significant error around 600 days is spread to wider ranges. From 392 days to 1008 days, the errors from CAC are all larger than 5%. However, the NMD errors are no more than 3%. On even larger scales (greater than 2000 days) the error caused by crossover around 600 days decreases. In the fitting range from 200 days to 20 years there is a non-significant difference of DFA exponents (Table 2) from two methods. Therefore we have reasons to believe that the missed inter-annual variability with changing AC amplitude would truly introduce an artificial bump and may cause an overestimation or underestimation of the long-term correlation in different scaling ranges. Since we only take the changing amplitude of annual cycle into account, the minor imperfect overcorrection from NMD is acceptable (actually, we can not see the difference between the result from NMD and the referential one from log-plot of $F(s)$ vs.s).

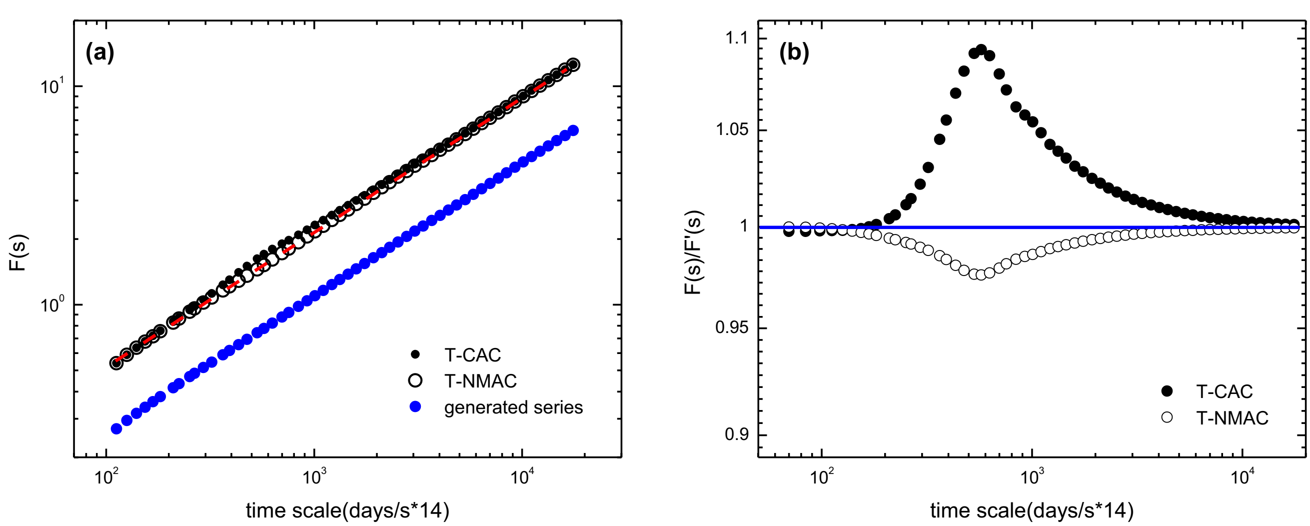

Fig. 8 The DFA results of artificially generated temperature series **a, b**, for clarity, *blue line* has been vertically shifted, where *black solid dots* for results from CAC filtering, *hollow circles* for results from NMAC filtering, *blue line* and *solid dots* for results from idealized series without annual cycles and *red dash line* for eye-guided scaling range

Table 3 DFA exponent error in different fitting ranges with lower limit of 100 days

Upper limit (day)	210	294	392	532	630	700	840	924
CAC	1.33%	3.34%	6.24%	9.07%	9.69%	9.42%	8.32%	7.67%
NMD	1.11%	1.45%	1.84%	2.30%	2.36%	2.26%	1.94%	1.75%
	1008	1932	3052	4032	4844	5824	7014	8428
CAC	7.04%	3.11%	1.33%	0.62%	0.25%	0.05%	0.29%	0.49%
NMD	1.58%	0.55%	0.12%	0.05%	0.13%	0.20%	0.25%	0.29%

4 Summary and discussion

In this paper, we have studied the impacts from inter-annual variability of climate annual cycle with changing amplitude on the estimation for long-term correlation. By comparing the observation, climatological annual cycle (CAC) and NMAC extracted by NMD method, the weakness of classical CAC is easy to outline. Sharing the same mean state of annual cycle with NMAC, CAC cannot reflect the inter-annual changes found in NMAC. If the inter-annual variability is not detected in annual cycle, the variation of this part may bias the anomaly's definition. In other words, variability of the annual cycle will be taken as variability of anomaly mistakenly. And this will result in an artificial bump around 600 days in line of log-plot of $F(s)$vs. s. Because of this artificial bump, the estimation would deviate from the true value when different fitting scaling range is determined.

To verify the assumption above, an idealized experiment from generated series with known long-term correlation is conducted. We create an artificial temperature series with changing amplitude of annual cycle and a long-term correlated anomaly series with α=0.6. The results show that CAC cannot capture the feature of changing annual cycle and leads to a same bump in the DFA curve. Although NMD method is also not perfect to overcome this drawback, it performs much better than CAC on the whole.

Why does this bump occur and how can we remove it? Since the inter-annual variability with changing AC amplitude has not been extracted by CAC, the anomaly part includes superfluous information so that the annual period component is not totally removed. Taking Bologna as an example, the Fast Fourier Transform (FFT) analysis indicates that original temperature records contain two dominated periods with two peaks for annual and semi-annual cycles (Fig. 9). It is supposed that no peak will be found after subtracting annual cycle (CAC or NMAC). However, the first period corresponding to 1-year cycle still remains in the FFT analysis of anomalies obtained by CAC. Despite the low magnitude it has, this period would definitely influence the calculation of LTM. Furthermore, presenting the FFT results in logarithmic coordinates (Fig. 10), dips in the multiplier frequencies of 1 year emerge clearly. These dips destroyed the structure of original records so that they can also influence the characteristics of the data.

CAC will leave out a part of periodical signal in the anomaly series due to the changing amplitude of annual cycle, so that anomaly series may still exhibit seasonal behavior of a different kind (Qian et al. 2011b, see their Fig. 4e; Graves 2013). Recently some new methods have been proposed to estimate the seasonal LTM (Graves 2013; Graves et al. 2017). In this work, the original records still have been decomposed into annual cycle and anomaly traditionally. The NMD method works fairly well in extracting the characteristics of time-varying annual cycle with changing amplitude (some other methods, such as EEMD can also serve this purpose, see Fig. 4 in Qian et al. 2011b) and can overcome the drawback from CAC quite well. Although it seems a little overcorrected (less than 3%) in the calculation of LTM, the results indeed indicate that the inter-annual variability of the time-varying AC plays an important role in the estimation of LTM. Since the annual cycle actually suffers from both amplitude and phase changes which may be caused by various reasons as reviewed in the introduction, taking the changing phase

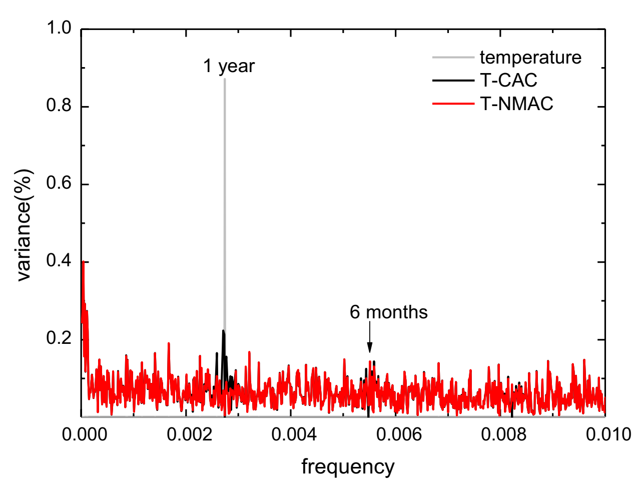

Fig. 9 Fast Fourier Transform analysis of the temperature records and anomalies at Bologna

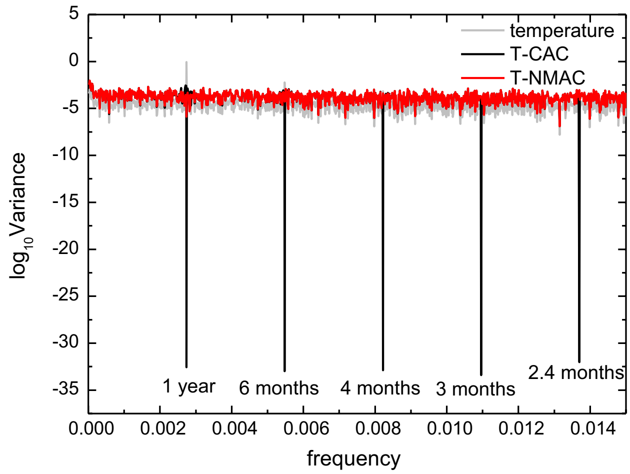

Fig. 10 Fast Fourier Transform analysis in logarithmic coordinates

into consideration could eliminate the left overcorrection possibly. This will be answered in the future works.

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