**Atmospheric
Chemistry
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Discussions**

Discriminating low frequency components from long range persistent fluctuations in daily atmospheric temperature variability

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Abstract

This study originated from recent results reported in literature, which support the existence of long-range (power-law) persistence in atmospheric temperature fluctuations on monthly and inter-annual scales. We investigated the results of Detrended Fluctuation Analysis (DFA) carried out on twenty-two historical daily time series recorded in Europe in order to evaluate the reliability of such findings in depth. More detailed inspections emphasized systematic deviations from power-law and high statistical confidence for functional form misspecification. Rigorous analyses did not support scale-free correlation as an operative concept for Climate modelling, as instead suggested in literature. In order to understand the physical implications of our results better, we designed a bivariate Markov process, parameterised on the basis of the atmospheric observational data by introducing a slow dummy variable. The time series generated by this model, analysed both in time and frequency domains, tallied with the real ones very well. They accounted for both the deceptive scaling found in literature and the correlation details enhanced by our analysis. Our results seem to evidence the presence of slow fluctuations from another climatic sub-system such as ocean, which inflates temperature variance up to several months. They advise more precise re-analyses of temperature time series before suggesting dynamical paradigms useful for Climate modelling and for the assessment of Climate Change.

1 Introduction

The traditional stochastic approach to climate approximation is mostly based on the concept of "scale separation" (Hasselmann, 1976). The basic idea of such an approach is that climatic variability can be interpreted on the basis of a set of cycles and characteristic time scales which account for a concentration of variance in relatively well-separated spectral bands. The most direct consequence of this assumption is the well-known separation between weather and climate: fast meteorological fluctu-

ations, which are intrinsic to the atmosphere, are mostly uncorrelated over long time periods; the accumulation of variance on low frequencies (redness) is in fact due to slow-responding climatic sub-systems such as oceans, ice cover and so on.

In the stochastic framework, meteorological variability has been traditionally explained by low-order autoregressive processes such as the paradigmatic first-order autoregressive process (AR1):

$$x_i = ax_{i-1} + \varepsilon_i \tag{1}$$

where x_i is the meteorological variable, a is the first-order autocorrelation coefficient, and ε_i represents uncorrelated Gaussian noise (white noise). According to this model, which assumes completely stationary external conditions, the parameter a accounts for a rapid exponential correlation decay so that the asymptotic behaviour, starting from scales of a few weeks, is uncorrelated and unpredictable: $x_i \sim \varepsilon_i$.

More recently, in the wake of the great success of empirical fractal tools devised for enhancing power-law correlation in noised and biased observational data (e.g., Peng et al., 1995; Konscielny-Bunde et al., 1998; Freeman et al., 1999; Matsoukas et al., 2000;. Haggerty et al., 2002; Bunde et al., 2002; Kandelhadrt et al., 2003, Blender and Fraedrich, 2003; Kandelhardt et al., 2006), Fractional Gaussian Noise (FGN) (Mandelbrot and van Ness, 1968) has been suggested as a realistic model for explaining the statistical dependence of atmospheric temperature anomalies (deviations from the mean annual trend) on climatic time scales (e.g., Konscielny-Bunde et al., 1996; Konscielny-Bunde et al., 1998; Govindan et al., 2001; Eichner et al., 2003; Kurnaz, 2004). The FGN correlation expresses a scale-free interdependence $c(t)=t^{-\gamma}$ ($0<\gamma<1$) and, for $\gamma>0.5$, the process is classified as persistent since the theoretical correlation implies non-zero probability that disturbances survive for times as long as infinite (long-range memory). This picture is truly different from that described by the exponentially decaying correlation $c(t)=\exp(-t/\tau)$. This has a characteristic time scale τ and short memory, since the mean life time of the disturbances has a finite value τ. The correlation functional form on long time scales reveals the deep dynamic nature of the interactions between atmosphere and other climatic components. Therefore, a

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correct assessment of this function provides useful insights for Climate modelling, also within a non-stochastic approach to the problem.

Most of the studies reported above agree on the presence of power-law persistence, which emerges after the meteorological correlation is decayed ($\sim$20 days) and goes on for several years. Therefore long-range correlation has been suggested as an operative concept for Climate modelling (Govindan et al., 2002). Atmospheric temperature variability is often cited as an example of fractal natural process despite the contradictory results about the universality of the scaling and the dependence of the exponent on sea distance (e.g., Vyushin et al., 2004a; Blender and Fraedrich, 2004; Vyushin et al., 2004b) as well as the existence of many drawbacks in the methodologies adopted (e.g., Hu, 2001; Kantelhardt, 2001; Metzler, 2003; Mauran et al., 2004; Gao et al., 2006, Rust, 2006).

The approach of the studies on this subject is the same. In practice, they try to establish whether the asymptotic noise ε_i in Eq. (1) is really uncorrelated or shows long-range correlation. Only two possibilities are considered in the long term: white noise or FGN. This point of view is well-expressed in the work by Király and Jánosi (2002). Since white noise (null hypothesis) is a trivial scale invariant, power-law is expected in both the cases; the only difference being in the numerical value of the exponents. Therefore, the actual descriptive skill of the power-law is not verified.

Nevertheless, the ability of low-order autoregressive processes to describe fast atmospheric variability lies in the concept of scale separation itself. AR1 is a reasonable model on "meteorological time-scales" where possible slower mechanisms which drive correlation do not induce remarkable variations. In other words, ε_i represents asymptotic weather and not climate.

In order to support long-range persistence against short memory it is not sufficient to exclude white noise. Since fractal tools are extremely sensitive to any kind of non-stationary behaviour (Gao et al., 2006), this is a necessary but not sufficient condition and alternative correlation structures should be explicitly excluded.

Here we analysed atmospheric temperature time series in order to investigate the re-

liability itself of the power-law fitting strategy. We applied Detrended Fluctuation Analysis (DFA) (Peng, 1995) to twenty-two atmospheric temperature time series recorded in Europe in order to investigate the estimated power-law persistence minutely. Some of these (Prague, St. Petersburg, Vienna, Potsdam) had already been analysed in literature. We focused on patterns described by the residuals from the best fits in order to verify that they have the random character expected in the case of appropriate fitting function. Since our results indicated instead functional form misspecification for the power-law approximation, we tried to evaluate whether the empirical results were consistent with the presence of a short-memory slow component beyond meteorology. To this aim, we built up a bivariate Markov process on the basis of the observational data and repeated the analyses on simulated time series, too. Our final goal was to demonstrate that a single time-scale, longer than the meteorological one, provides a satisfactory description of the sample correlation and is sufficient for tricking fractal tools by generating a deceptive fractal regime like that observed in atmospheric temperature time series.

2 Detrended Fluctuation Analysis of temperature anomalies

2.1 Methods

2.1.1 Detrended Fluctuation Analysis

We used the Detrended Fluctuation Analysis, which is one of the most utilized tools for minimizing externally-induced non-stationary effects describable in the form of low-order polynomials (Peng et al., 1995). We shortly recall how this methodology works. The time series to be analysed is integrated and divided into N boxes of length n. In each box, a least square polynomial $y_n(k)$, representing the trend in that particular box, is fitted to the integrated data $y(k)$. Then, the root-mean-square fluctuation

$F(n) = \sqrt{\sum_{k=1}^{N} [y(k) - y_n(k)]^2 / N}$ is calculated. This computation is repeated on many time-scales (box sizes) in order to characterize $F(n)$ as a function of n. Power-law (fractal) scaling implies a linear relationship in a log-log plot. Under such conditions, fluctuations can be characterized by a scaling exponent α ($\gamma = 2 - 2\alpha$ for FGN). The value $\alpha = 0.5$ is expected for uncorrelated noise, and values $\alpha > 0.5$ characterize persistent time series.

In this work we have adopted the 2nd-order detrending (DFA2) in order to minimize the effects of discontinuities and linear trends.

2.1.2 Runs test

The Runs Test (Bradley, 1968) determines the probability P that a curve, a power-law in this specific case, deviates systematically from experimental data. A "run" is a consecutive sequence of points whose residuals are all either positive or negative. If there are N_+ and N_- points above and below the curve respectively, the number of runs R in the hypothesis of fully random residuals has mean value $\mu_R = 2N_+ N_- / (N_+ + N_-) + 1$ and variance $\sigma_R = (\mu_R - 1)(\mu_R - 2)/(N_+ + N_- - 1)$. The test is performed by estimating the probability that the value of the variable $Z = (R - \mu_R)/\sigma_R$, obtained from experimental data, belongs to the normal distribution. This Z-score expresses the divergence of the experimental result R from the most probable result μ_R as a number of standard deviations σ_R: the more negative the value of Z, the greater the probability of functional form misspecification due to a trend in the residuals. We wish to recall that a value $Z < -2$ is sufficient for excluding randomness with probability $P > 98\%$.

2.2 Data

DFA was applied to twenty-two time series (see Table 1) extracted from the ECA&D catalogue (Klein Tank et al., 2002), available at http://eca.knmi.nl/. In particular, the data recorded in Prague, St. Petersburg, Vienna, and Potsdam had already been anal-

ysed in literature (Konscielny-Bunde et al., 1998; Govindan et al., 2001; Eichner et al., 2003; Monetti et al., 2003; Mauran et al., 2004). By following the procedure adopted in these studies, we analysed temperature anomalies (deviations form the mean annual cycle).

3 Results

Figure 1 shows the results of DFA2 applied to the four observational time series already analysed in literature. Plots seem to agree with slightly persistent FGN on time-scales starting from a few weeks, in a complete agreement with previous studies.

Temperature anomalies are basically unpredictable on such scales and possible non fractal correlations should explain very low percentages of variance. In this case, $F(n)$ is expected to describe patterns close to the trivial background power-law $n^{0.5}$. However, although small, hypothetical departures from the fractal behaviour should exhibit systematic features. In order to check the correctness of the fractal model, we focused on local details which are lost in the log-log plots of $F(n)$. If the power-law fit n^{α} is right, the ratio $F(n)/n^{\alpha}$ is constant in theory, and its values estimated on observational data are expected to show uncorrelated variability. Instead, such a ratio is strongly patterned in a non-linear way (Fig. 2). The unfitting character of the scale invariant paradigm is especially evident on sub-annual scales where non-linearity is particularly impressive.

Although the simple naked eye inspection of our results was sufficient to draw conclusions on the misrepresentation of the power-law, we applied the Runs Test in order to quantify the goodness of fit. Table 1 shows the power-law exponents and the values of the variable Z for all the twenty-two time series. Note that all the estimated values of Z are less than -90. This means that the number of runs is placed at a distance greater than $90\sigma_R$ from the mean value μ_R expected for random residuals; its value is always dramatically less than that expected for a reliable fitting function. If the data were randomly scattered above and below the power-law, the probability of observing so few runs in all the examined cases was $P \cong 0$. In practice, the data were fitted to the

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wrong equation.

As a simple alternative, it is also possible to evaluate the consistency of the fluctuation function with the scaling law $F(kn)=k^{\alpha}F(n)$. Such a relation should hold for any n and kn within the range of the scaling regime. Figure 3 shows, as an example, the plot of $\alpha(n)=\log_2(F(2n)/F(n))$ whose theoretical value should be constant for any n higher than $\sim$20 days. Once again, the results show a continuous change of the local exponent, which is close to 1 for short time-scales and decays progressively while approaching a final very irregular regime. Altogether, these findings show that the agreement between sample estimations and power-law is merely apparent since more thorough investigations enhance functional form misspecification. From a physical point of view, a systematic decay of $\alpha(n)$ suggests a dependence on scale and confirms that the fractal paradigm is not suitable for describing the actual temperature variability on the scales investigated.

4 A bivariate Markovian simulation of daily atmospheric temperature anomalies

4.1 Model development

The simplest short memory multivariable model, which might be able to approximate atmospheric temperature variability, is the bivariate Markov process which has been suggested, as an example, to describe coupling phenomena between atmosphere and sea surface temperature (SST) (e.g, Mosedale et al., 2005):

$$\begin{cases} T_i = a_{11}T_{i-1} + a_{12}S_{i-1} + \sigma_\varepsilon \varepsilon_i \\ S_i = a_{21}T_{i-1} + a_{22}S_{i-1} + \sigma_\eta \eta_i \end{cases} \tag{2}$$

where T_i is daily temperature anomaly; ε_i and η_i are normally distributed white noises; the 2×2 matrix (a_{ij}), σ_ε, and σ_η are the model parameters; and S_i denotes SST. According to the model above, the process $\zeta_i=a_{12}S_{i-1}+\sigma_\varepsilon\varepsilon_i$ represents innovations for T_i. On scales greater than the meteorological one, local persistence exponents could

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be detected since the correlation of T_i is mainly dominated by that of S_i, which is characterized by the slower variability of the oceans.

Here we followed the suggestion provided by Model (2) and tried to build up a bivariate Markov process able to roughly reproduce temperature statistical dependence. We would like to clarify that our goal was rather general. We aimed at evaluating whether plausible mechanisms alternative to long-range memory are able to reproduce the observed persistence, and to trick fractal tools. Thus, we kept the symbol S_i to denote the twin variable of T_i in the bivariate model, specifying that it does not necessarily represent SST. We simplified the problem by eliminating the feedback of T_i on S_i ($a_{21}=0$) so as to handle S_i as a truly external forcing of unknown origin. Covariances $\gamma(k)_{ij}$ at any lag time k were generated recursively by using scalar relations (Jenkins and Watts, 1968) which, in the hypothesis $a_{21}=0$, are:

$$\gamma_{22}(k) = a_{22}\gamma_{22}(k-1)$$

$$\gamma_{12}(k) = a_{22}\gamma_{12}(k-1) \quad k \geq 1 \tag{3}$$

$$\gamma_{11}(k) = a_{11}\gamma_{11}(k-1) + a_{12}\gamma_{12}(k-1)$$

with initial values:

$$(1 - a_{22}^2)\gamma_{22}(0) = \sigma_\eta^2$$

$$(1 - a_{11}a_{22})\gamma_{12}(0) = a_{12}a_{22}\gamma_{22}(0) \tag{4}$$

$$(1 - a_{12}^2)\gamma_{11}(0) = \left(a_{12}^2\gamma_{22}(0) + 2a_{11}a_{12}\gamma_{12}(0) + \sigma_\varepsilon^2\right)$$

The theoretical model was parameterised by fitting sample temperature autocorrelation to the function $\rho_{11}(k)=\gamma_{11}(k)/\gamma_{11}(0)$, which represents the autocorrelation of the component T_i. As a trainer for our model we used the time series recorded in Prague which is the longest among those illustrated in the previous Section. An increasing trend associated to urban warming (Govindan et al., 2001) is likely to be the main responsible

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for the slow decay of the autocorrelation $\hat{\rho}(k)$ estimated for this time series (see Fig. 4). In fact, the first autocorrelation coefficient which falls within the 95% confidence interval for zero correlation ($\sim$0.007) is estimated for k=1210 days but, if we compute $\hat{\rho}(k)$ by using only the first 100 years of the time series, this first value is estimated for k=155 days. Here we assumed that the effect of the trend on autocovariance for time-scales of a few years is approximately the addition of a non-zero asymptotic constant. So, we represented the fitting autocorrelation in the form $\tilde{\rho}(k)=\rho_{11}(k)+\rho_0$ and determined the model parameters by minimizing the root-mean-square error $E=\sqrt{\sum_{k=1}^{M}(\tilde{\rho}(k)-\rho(\hat{k}))^2/M}$, where M=3650 days (ten years). In any case, we specify that only the function $\rho_{11}(k)$ was used in the simulations.

The results of the minimizing procedure provided the best fit coefficients (a_{11}=0.74, a_{12}=0.06, a_{22}=0.98, σ_ε=0.98, σ_η=0.39, ρ_0=0.01) and the autocorrelation function $\tilde{\rho}(k)$. We considered the optimal agreement between $\tilde{\rho}(k)$ and the temperature sample autocorrelation $\hat{\rho}(k)$ quite satisfactory for our general purposes (Fig. 4) and sufficient to continue with time series simulation. Obviously, the autocorrelation $\hat{\rho}_{11}(k)$ of the time series generated by the model decays faster than the total theoretical autocorrelation $\tilde{\rho}(k)$ due to the absence of the trend contribution, but the comparison of the power spectra (Fig. 5) evidences a good qualitative performance of our model despite the lack of this contribution.

4.2 Comparison between real and synthetic data

Figure 6 shows the results of DFA2 applied to real and synthetic data. The agreement is very impressive. No evidence of any significant difference of dynamical value on the investigated scales was found in repeated Markovian simulations. Figure 7 shows the residuals from power-law and the estimates of $\alpha(n)$ for the synthetic series of Fig. 6. Also in this case the agreement with the results obtained for real data (Figs. 2 and 3) is very evident.

Simulated time series account for common properties of atmospheric temperature anomalies even if they are intrinsically not fractal. DFA is just tricked by the separation between the two scales governing T_i. Figure 8 shows this effect on the fluctuation function of the process $\zeta_i = a_{12}S_{i-1} + \sigma_\varepsilon \varepsilon_i$, which represents innovations for the process

5 T_i. Due to the strong correlation of S_i, $\sigma_\zeta^2 \sim \sigma_\varepsilon^2$ on the shortest time scales and the slope is about 0.5, as expected for weather on uncorrelated scales. Also on long asymptotic scales such innovations are uncorrelated, but here the explained variance is slightly greater than the initial one: $\sigma_\zeta^2 = a_{12}\sigma_S^2 + \sigma_\varepsilon^2$. This hidden increase also causes the increase in the fluctuation function of T_i and the overall effect is an apparent uniform

10 scaling. Note that also S_i is able to produce a long lasting power-law (about 2 decades). The slope of this apparent scaling is $\alpha = 1.4$, which curiously agrees with the values estimated on the same time-scales for the North Atlantic SST (Monetti et al., 2003).

5 Conclusions

The crucial result of our work was that the existence of long-range memory mecha-

15 nisms in atmospheric temperature fluctuations on time-scales ranging from weeks to several years has not been demonstrated yet. On such scales, where previous studies claimed the evidence of power-law correlation, persistence exponents vary with the scale instead. A simple search for straight lines in a log-log plot is not sufficient for assessing long-range correlation and the reliability of the proposed correlation functional

20 form should be explicitly tested. Moreover, a simple bivariate Markov model is able to account for the whole results, apparent scale invariance included.

More in general, the model derived in this work represents one of the many possible dynamical scenarios which can trick fractal tools. Therefore, more precise re-analyses of temperature time series are required before suggesting dynamical paradigms useful

25 for Climate modelling and for the assessment of Climate Change.

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Table 1. Historical time series: estimated power-law coefficients α obtained from DFA2 and relative Z-scores for random residuals probability. The considered time-scale range is $20 \div 10^4$ days; errors on α are less than 0.001.

| Station	Record	α	Z
Wien (AT)	1901–2004	0.63	−97
Sarajevo (BA)	1901–2004	0.55	−98
Uccle (BE)	1833–1999	0.61	−95
Basel Binningen (CH)	1901–2004	0.60	−97
Lugano (CH)	1901–2004	0.61	−98
Saentis (CH)	1901–2004	0.56	−98
Zuerich (CH)	1901–2004	0.60	−98
Prague (CZ)	1775–2004	0.63	−96
Bamberg (DE)	1879–2001	0.63	−97
Hamburg (DE)	1891–2001	0.63	−96
Hohenpeissenberg (DE)	1879–2001	0.58	−98
Potsdam (DE)	1893–2001	0.63	−96
Marseille (FR)	1900–2002	0.58	−98
Paris (FR)	1900–2004	0.59	−96
Zagreb (HR)	1862–2001	0.58	−97
Bologna (IT)	1814–2003	0.62	−96
Milan (IT)	1763–2003	0.67	−98
De Bilt (NL)	1901–2004	0.64	−96
Eelde (NL)	1907–2004	0.66	−97
Maastricht (NL)	1906–2004	0.58	−95
St. Petrsburg (RU)	1881–1998	0.66	−97
Stockholm (SE)	1756–1999	0.67	−97
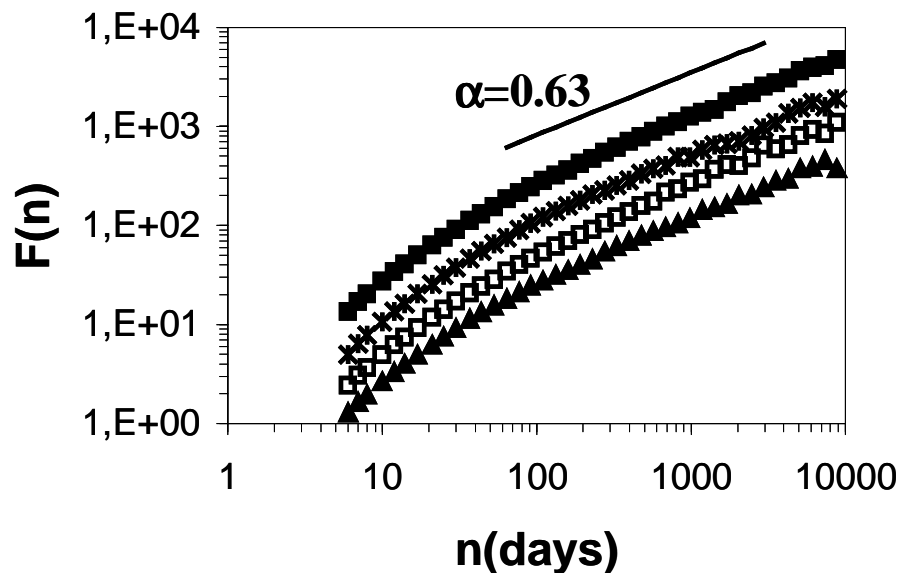
Fig. 1. DFA results for four temperature anomaly time series. From the top to the bottom: Prague (filled squares), Wien (stars), St. Petersburg (empty squares), Potsdam (triangles). Continuous line shows the theoretical power-law $n^{0.63}$ ($\alpha=0.63$; $\gamma=0.74$) obtained from the power law best fits of $F(n)$ in the range $20 \div 10^4$ days. The error on the estimated value of α was less of 0.001 in all the cases. Plots were shifted vertically to separate the patterns.
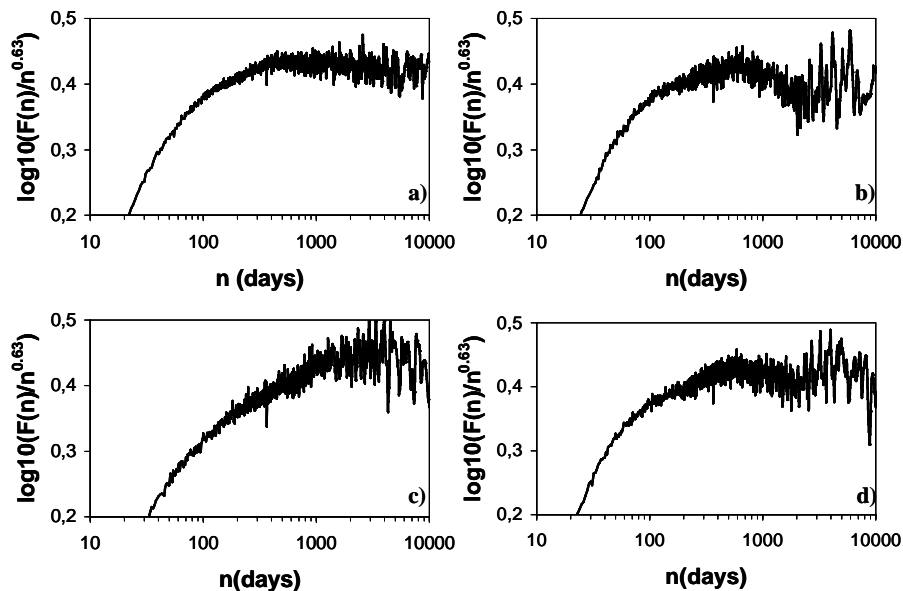
Fig. 2. Plots of the ratio $F(n)/n^{\alpha}$ in logarithmic scale for the four time series of Fig. 1: **(a)** Prague; **(b)** Wien; **(c)** St. Petersburg; **(d)** Potsdam.

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Interactive Discussion
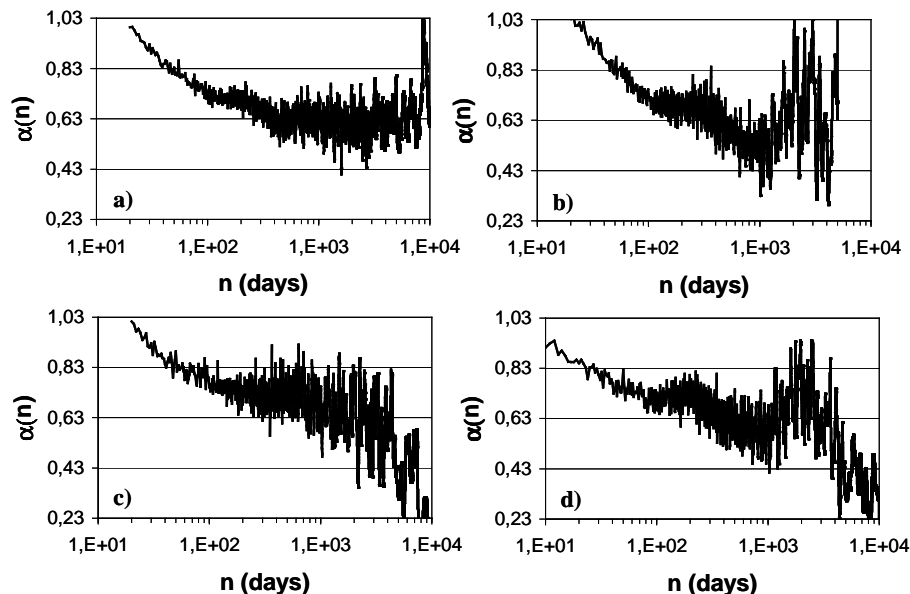
Fig. 3. Plots of the function $\alpha(n)$ for the four time series of Fig. 1: **(a)** Prague; **(b)** Wien; **(c)** St. Petersburg; **(d)** Potsdam.
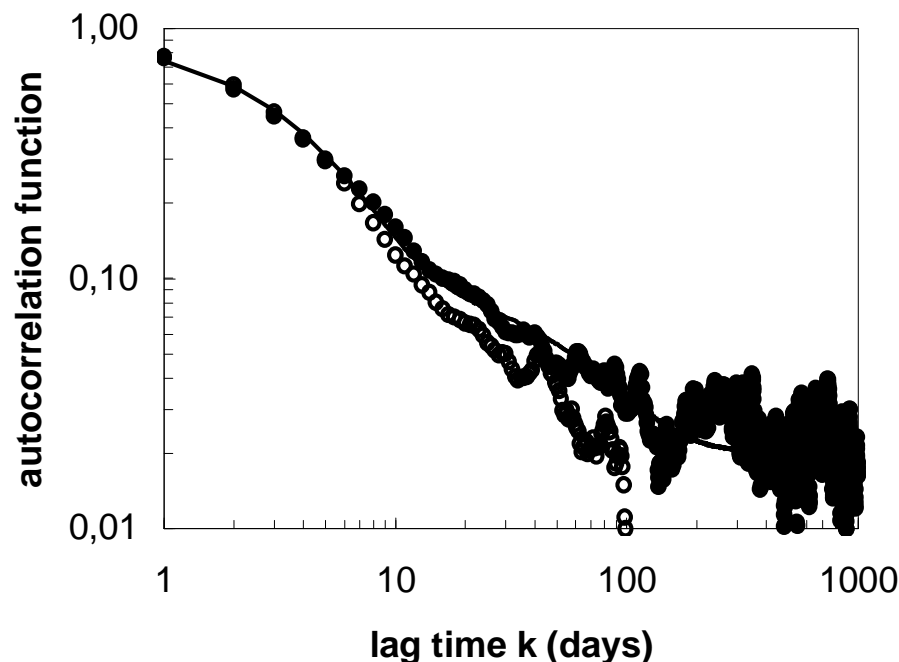
Fig. 4. Estimated autocorrelation function $\hat{\rho}(k)$ of observational anomalies (filled circles); autocorrelation function $\tilde{\rho}(k)$ of the bivariate process contaminated by a linear trend (continuous line); estimated autocorrelation function $\hat{\rho}_{11}(k)$ in the absence of trend (empty circles). The 95% confidence band ($\sim$0.007) does not exceed the size of the symbols.
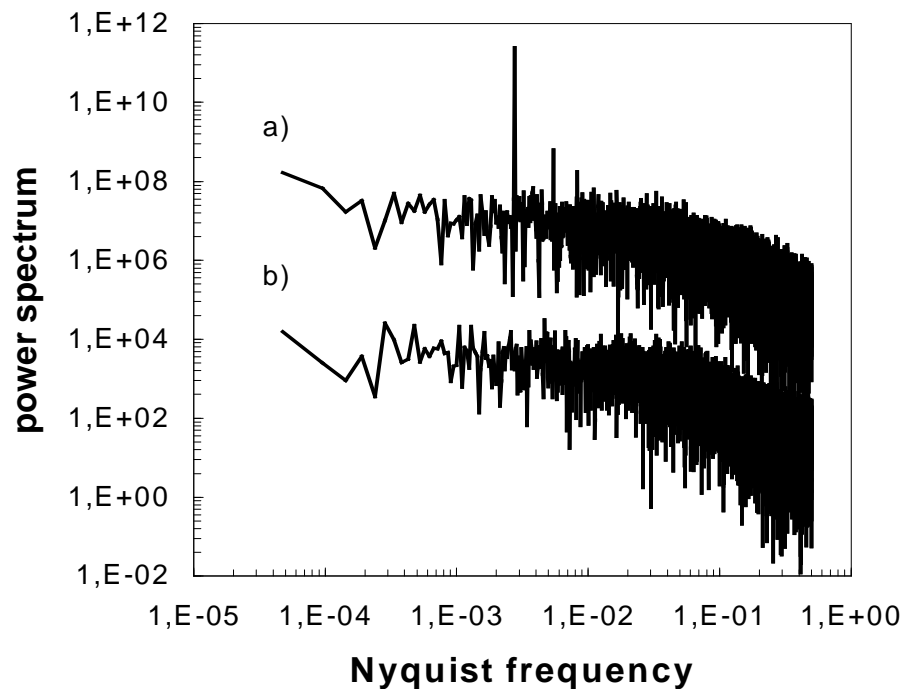
Fig. 5. Power spectra of: **(a)** real temperature measures (annual cycle included) and **(b)** synthetic data. Plots were shifted vertically to separate the two patterns.
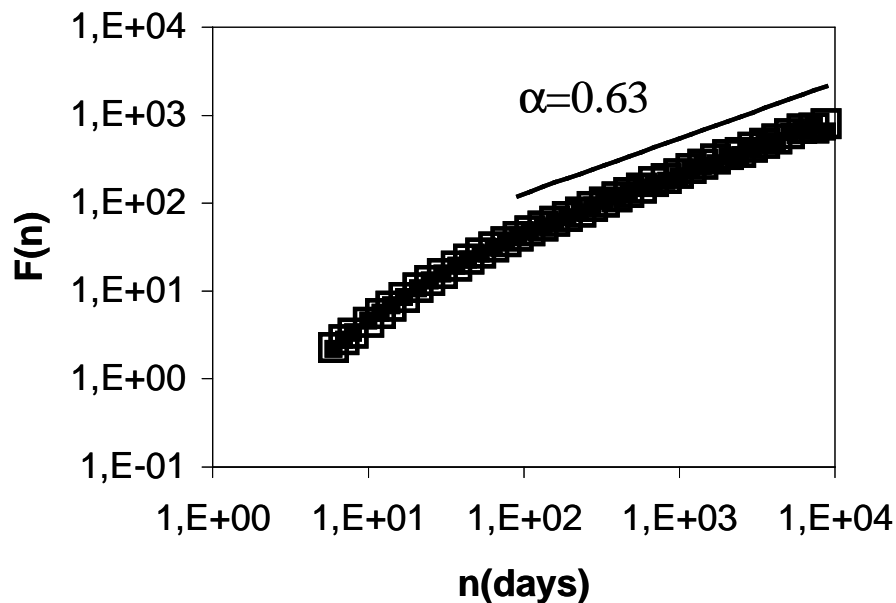
Fig. 6. Results of DFA for real (filled squares) and simulated (empty squares) anomalies. Continuous line shows the theoretical power law. The error on the estimated value of α was less of 0.001 in both the cases.
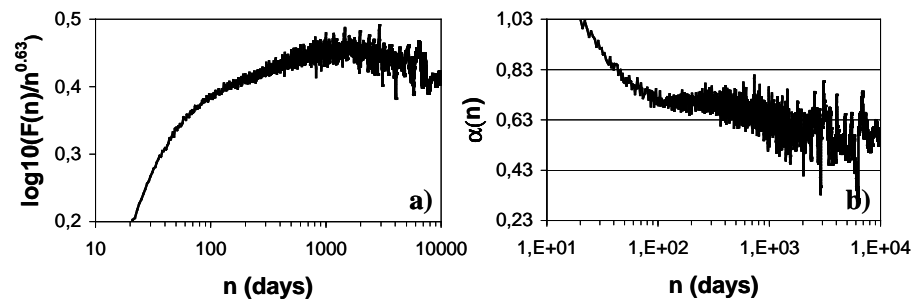
Fig. 7. As in Figs. 2 and 3 but for synthetic data: **(a)** $F(n)/n^{0.63}$ in logarithmic scale; **(b)** $\alpha(n)$.
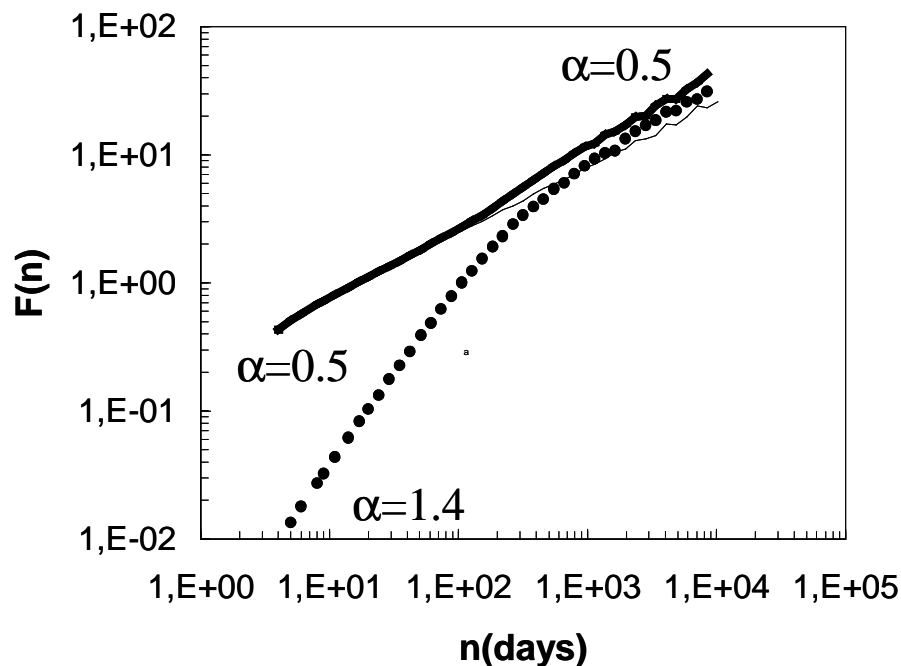
Fig. 8. Results of DFA for ζ_i (bold solid line), ε_i (solid line), and S_i (circles). ζ_i behaves as a white noise on short time scales and approaches a white noise with larger variance on the longest ones. This difference in variance between the extreme regimes of the innovations creates the illusory existence of persistence in simulated temperature variability.