Nonuniversal atmospheric persistence: Different scaling of daily minimum and maximum temperatures

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An extensive investigation of 61 daily temperature records by means of detrended fluctuation analysis has revealed that the value of correlation exponent is not universal, contrary to earlier claims. Furthermore, statistically significant differences are found for daily minimum and maximum temperatures measured at the same station, suggesting different degrees of long-range correlations for the two extremes. Numerical tests on synthetic time series demonstrate that a correlated signal interrupted by uncorrelated segments exhibits an apparently lower exponent value over the usual time window of empirical data analysis. In order to find statistical differences between the two daily extreme temperatures, high frequency (10 min) records were evaluated for two distant locations. The results show that daily maxima characterize better the dynamic equilibrium state of the atmosphere than daily minima, for both stations. This provides a conceptual explanation why scaling analysis can yield different exponent values for minima and maxima.

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I. INTRODUCTION

Understanding long-range temporal correlations in the atmosphere is of fundamental interest: it is far from being a purely academic question whether the observed warming trend is a consequence of human interference or it is a normal "excursion" of the variable climate [1]. Each of the most elaborated global coupled atmosphere-ocean models indicates that recent warming is likely to continue, regardless of the computer model used or the emission scenario applied [2]. However, it is not entirely clear how far can we trust in the prediction skills of global climate models. For example, a recent test by Govindan *et al.* [3] of seven state-of-the-art models failed to reproduce the scaling behavior of six measured surface temperature records by underestimating the long-range persistence of the atmosphere. Similar discrepancies were detected already by Syroka and Toumi [4], and later Vjushin *et al.* [5]. On the other hand, Fraedrich and Blender [6] demonstrated that an improved model setup with a constant greenhouse gas environment does reproduce atmospheric scaling extending up to centuries. They also emphasize that a detailed analysis of empirical long-range correlations is indispensable [6]. Indeed, direct comparison of local observations with the rather low resolution general circulation models does have many pitfalls [7].

Various methods are used to characterize quantitatively the fluctuations and correlations of high frequency meteorological data. Besides power density spectra, autocorrelation functions, Hurst rescaled ranges, etc., the relatively new method of detrended fluctuation analysis (DFA) has been proven useful in revealing the extent of long-range correlations in diverse time series [8]. DFA and the more traditional methods provide equivalent characterizations of correlated stochastic signals [9–11], with the essential difference that DFA can effectively filter out nonstationarities such as slow trends.

Variations in surface air temperature is obviously one of the most fundamental indicators of fluctuations or changes in climate. The longest continuous daily records of measured air temperatures extend back to the eighteenth century, therefore such data sets are favorite subject of time series analysis. Asymptotic scaling has been identified for several long records [3,9,10,12,13], shorter-time correlations are usually explained by using first- or second-order linear autoregressive models [14,15]. Koscielny-Bunde *et al.* [9] believed to observe a universal correlation exponent for continental stations. Subsequent DFA studies by Weber and Talkner [13] and Monetti *et al.* [16] indicated significant variance for stations of different climatic parameters. Recent comprehensive analyses by Fraedrich and Blender [6] and Király and Jánosi [17] unambiguously revealed strong dependence on geographic location. Furthermore, we show here that even daily minimum and maximum temperatures at a given station can exhibit different asymptotic scaling. In order to get a clue for such behavior, we analyze two temperature records with temporal resolution of 10 min. We illustrate that the representation of an atmospheric equilibrium temperature by daily minima is inferior to daily maxima for the particular stations.

II. NONUNIVERSAL SCALING

The first part of our analysis is based on a high-quality measured daily temperature set for Australia [18,19]. Data for 61 (out from 99) stations were selected according to the quality of their climate record, in terms of site standards, homogeneity, and completeness of the series, and to provide the best possible spatial coverage (48 for the continent, 13 for islands).

The most important advantage of DFA over conventional methods is that it permits the detection of intrinsic self-similarity embedded in a seemingly nonstationary time series. Following the work of Peng *et al.* [8], several theoretical studies elucidated the power and limitations of filtering out various trends from synthetic data series [10,11,20–22]. One of their main findings is that DFA results for signals

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with different correlation properties and background trends can be fully explained by the assumption of variance superposition [20,22]. This is essential because the correlation exponent as a function of time segment length is almost never constant for any real data, crossover(s) can usually arise from a change in the correlation properties at different time scales or as a consequence of trends. Other types of nonstationarities are missing segments in records (very common), contamination with random spikes, or signals with different local behavior (different variance or local correlations).

As a first step of DFA analysis, the annual cycle is removed from the raw data T_i by computing the temperature anomaly series $x_i = T_i - \langle T_i \rangle_d$, where $i = 1, \ldots, N$, and $\langle \cdot \rangle_d$ denotes the long-time average for the given calendar day. Next, the anomaly series is integrated to obtain the so-called profile $y_j = \Sigma_{i=1}^{j} x_i$. The profile is divided into nonoverlapping time segments of equal length n, and the local trend is fitted by a polynomial of order p in each segment. The fluctuation $F_p(n)_k$ for the kth profile is determined as the root mean squared deviation from the local trend, an average $F_p(n)$ is formed over the different segments. A power-law relationship between $F_p(n)$ and n indicates scaling with an exponent δ (DFAp exponent):

$$F_p(n) \sim n^{\delta}. \tag{1}$$

Notice that such a process has a power-law autocorrelation function

$$C(\tau) = \langle x_j x_{j+\tau} \rangle \sim \tau^{-\alpha}, \tag{2}$$

where $0 < \alpha < 1$, and the relationship between the correlation exponents is [9,10]

$$\alpha = 2(1-\delta). \tag{3}$$

Long-memory (persistent) processes are characterized by DFA exponent $\delta > 0.5$, uncorrelated time series (e.g., pure random walk) obey $\delta = 0.5$, antipersistent signals exhibiting negative long-range correlations have $\delta < 0.5$.

We briefly show results for 48 daily *mean temperature* series for Australian continental stations analyzed in details in Ref. [17]. The average length of these records is 45 years, the shortest and longest are 22 and 120, respectively. In general, fitting was possible over more than two orders of magnitude. We found asymptotic long-range correlations in the range 30–1800 days for each case, the scaling regime extends up to ten years for the longer records. In strong contrast to earlier claims on a universal exponent value [3,9] we found pronounced station dependence, similarly to Fraedrich and Blender [6]. We emphasize that weak trends were detected only in the longest temperature anomaly series (Sydney, Melbourne, Adelaide) which might be attributed to urbanization or global warming, but this question is beyond the scope of the present work. Even for these cases, DFA2 exponents could not be distinguished from DFA1 values within the fitting error.

Figure 1 illustrates how the value of correlation exponent δ depends on the geographic location of the station. Two tendencies can be resolved in Fig. 1. First, the general trend is a decrease of exponents with decreasing latitude. Indeed, the contours of the fitted surface are almost parallel with the lines of latitude. This tendency is in complete agreement with the correlation properties of 500-hPa height anomalies in the northern hemisphere found by Tsonis *et al.* [23], however it is somewhat different from the results of Fraedrich and Blender [6]. (Note that the spatial resolution of their analysis is much lower for the given region, especially over the continent.) Second, there is a hump over the southeastern part of the continent which correlates well with the location of the highest mountain range (Australian Alps). We do not want to overemphasize this observation, nevertheless Weber and Talkner [13] found also higher exponent values for mountain weather stations.

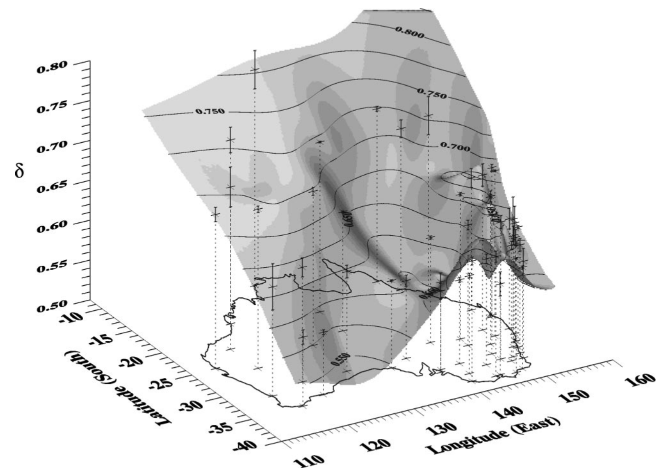

FIG. 1. Correlation exponent δ for daily mean temperature anomalies at the continental stations (48 altogether) as a function of geographic location. The contour of Australia is also indicated. (Error bars are shown as vertical lines.)

The overall behavior of temporal correlations for *daily minima and maxima* is practically the same as shown in Fig. 1, apart from numerical values. It is remarkable, however, that the correlation exponents for the daily extremes $\delta(x_{min})$ and $\delta(x_{max})$ can be different for a given station (Fig. 2), and the disparity is statistically significant in many cases: 27 out from 48 continental stations (56%), while 7 out from 13 for

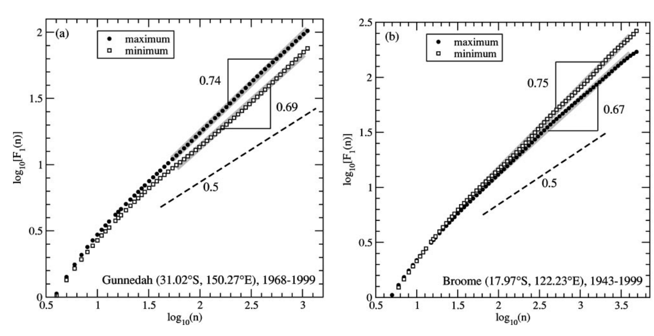

FIG. 2. Representative DFA1 results for daily minimum and maximum temperature anomaly series for two stations: (a) Gunnedah 1968–1999, 31.02°S, 150.27°E, and (b) Broome 1943–1999, 17.98°S, 122.23°E. Gray lines indicate linear fits, dashed line illustrates the slope for an uncorrelated process.

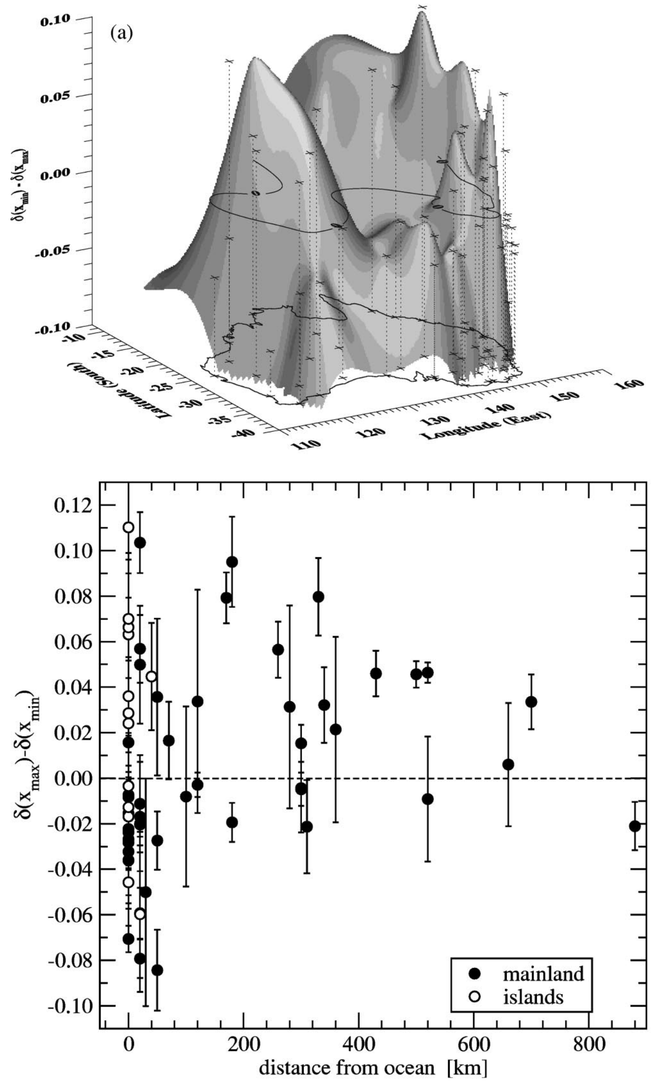

FIG. 3. Top: The difference of correlation exponents for daily maximum and minimum temperature anomalies $\delta(x_{max})-\delta(x_{min})$ as a function of geographic location. Bottom: The same as a function of distance from the closest seashore. Data for islands (not shown on the top) are denoted by empty circles. Error bars are obtained by Eq. (4).

islands (54%), see Fig. 3, bottom. (The low noise level in Fig. 2 is due to the standard ''sliding window'' technique, where local trend removal and variance computation for a given time window of length *n* were performed at each possible starting value $i=1,\dots,N-n$.) Error bars for the individual exponents are obtained by fits to different parts of the $\log[F_1(n)]$ vs $\log(n)$ curves, and the statistical error for the difference is estimated by the usual error propagation rule

$$\Delta[\delta(x_{max})-\delta(x_{min})]=\sqrt{[\Delta\delta(x_{max})]^2+[\Delta\delta(x_{min})]^2}. \tag{4}$$

Compared with the exponent values for daily mean temperatures $\delta(x_{mean})$, we could not identify any systematic pattern, apart from the fact that they fall into the interval defined by the maxima and minima:

$$\delta(x_{mean})\in[\delta(x_{max})+\Delta\delta(x_{max}),\delta(x_{min})-\Delta\delta(x_{min})]. \tag{5}$$

This is expected from the variance superposition assumption [20,22].

The representative examples in Fig. 2 might suggest that higher exponent values would be connected with higher level of variance at a given time segment *n*, i.e., the DFA curve of larger slope for a given extremum temperature runs above the curve for the other extremum. Detailed evaluation gave negative result: there is no correlation between variance level and the sign of the difference of exponents. Further statistical tests also failed to detect correlations with other characteristics such as the skewness and kurtosis of the amplitude distribution for the temperature anomaly fluctuations.

We also could not identify plausible pattern for a dependence on geographic position (Fig. 3). The results of correlation analysis with respect to the distance from seashore (Fig. 3, bottom), elevation, or longitude of the stations (not shown here) are also negative. This might be a consequence of sparsity of data from the middle of the continent. It is more probable that differences in the statistics of daily maxima and minima depend on subtle local details, such as soil, vegetation, moisture, etc. (Note that daily extremes are routinely determined by simple minimum-maximum thermometers, thus they are really sensitive to local fluctuations.)

III. CORRELATION EXPONENT TUNING

The results of the preceding section can be summarized as follows.

(i) Daily characteristic temperature values (minimum, maximum, arithmetic mean) have significant positive long-range correlations extending for several years. There is no sign of breakdown of scaling behavior even for the longest time series.

(ii) The ''degree'' of correlations, i.e., the value of correlation exponent is not universal, it depends on the geographic location.

(iii) There is a general tendency of decreasing exponent value with increasing distance from the equator over Australia.

(iv) The value of DFA exponent for daily minima and maxima can be different for a given station. The sign and magnitude of the disparity do not correlate with geographic or other statistical parameters, most probably they are determined by local circumstances (microclimate).

The lack of universality in the value of correlation exponent requires further explanations. It can be difficult to find a reasonable unique physical mechanism, therefore our aim here is to give a conceptual framework for a process family of continuously changing DFA exponents.

Systematic analyses by Hu *et al.* [20], Kantelhardt *et al.* [21], and Chen *et al.* [22] on various synthetic time series revealed many useful details on the diagnostic power of DFA. For example, a long-range correlated process with additive random noise can be easily identified, because its DFA curve has a crossover from a slope $\delta=0.5$ (noise dominated part) to a different asymptotic value. The crossover time de-

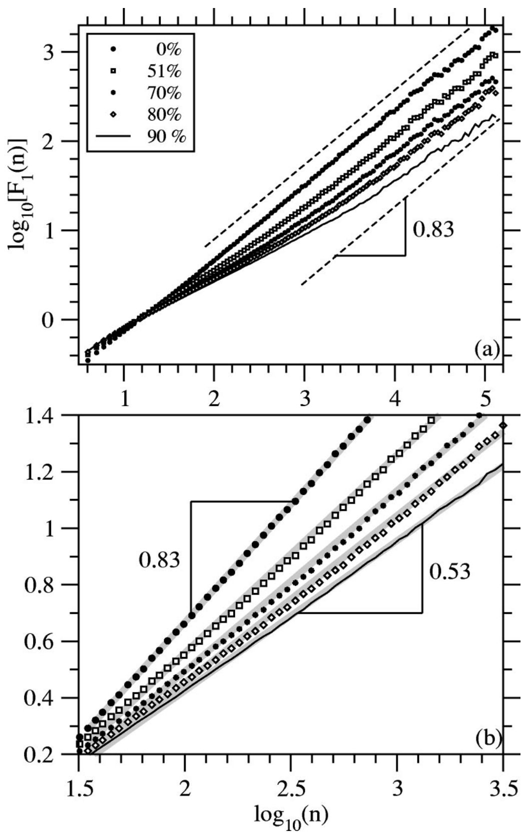

FIG. 4. (a) DFA1 curves in double-logarithmic scale for a correlated synthetic data set of length $N=524\,288$ with different amount of randomized replacements (see legends). Dashed lines indicate the "true" asymptotic slope. (b) The same as (a) zoomed into the range $n\in 30$–3000 days. Transient exponents are $\delta_{tr}=0.83$, 0.70, 0.64, 0.59, and 0.53, respectively. The asymptotic exponents ($n>10\,000$) are different for randomized data: $\delta_{as}=0.83$, 0.80, 0.76, 0.75, 0.67.

pends primarily on the variance of the random noise (large amplitude—later crossover) and on the correlation exponent of the underlying process (large exponent—earlier crossover). Furthermore, scaling of correlated data series ($\delta>0.5$) is not affected by randomly cutting out segments and stitching together the remaining parts, even when half the points is removed [22]. From our point of view, signals with different local correlations deserve special attention. In general, when random parts of a correlated data series are replaced by segments from another series of different correlation exponent, the behavior is dominated by the segments exhibiting higher positive correlations [22]. However, there is a wide transition regime with a nontrivial effective exponent, thus a "true" asymptotic behavior could be observed at extremely long time series only, especially when the difference between the exponents is small. This behavior is illustrated in Fig. 4.

Power-law correlated, normalized Gaussian data sets of length $N=2^{19}$ were generated with the algorithm developed by Pang, Yu, and Halpin-Healy [24]. For a given set, different amount of its total length was replaced by randomized segments of average duration $w=10$ "days" and of the same amplitude distribution. Typical DFA curves are shown in Fig. 4(a). Note that the transient toward the true asymptotic slope can be very wide. The common fitting range for existing temperature time series is $30<n<3000$ days (about one-fifth of the total record length); Fig. 4(b) illustrates that this part can be also approximated by a power law. Exponent values δ_{tr} obtained in this transient part are usually different from the large n slopes δ_{as}. The robustness of positive correlation is remarkable: 90% of the total length can be replaced with uncorrelated segments, notwithstanding the signal clearly indicates persistence. For more details see Ref. [22].

As we mentioned already, the decreasing tendency of empirical correlation exponents at decreasing latitudes (see Fig. 1) is in complete agreement with the results by Tsonis *et al.* [23] for 500-hPa height anomalies in the northern hemisphere. They attribute a decreasing degree of correlations to an increasingly baroclinic nature of the dynamics as one progresses from the subtropics through the midlatitudes. More baroclinicity results in more power to processes of small spatial and temporal scales. In this respect, a dynamics of increased baroclinicity means that an underlying correlated time evolution can be more often interrupted by short-memory, small scale processes yielding a decreased effective correlation exponent.

This explanation, however, cannot help to understand the difference between correlation properties of daily minimum and maximum temperatures for a given station. Nevertheless the argumentation above can give the hint to find different level of randomness in the records, if it exists at all. Time series of daily extremes are clearly not suitable for such analysis, because short, local segments cannot exhibit long-range correlations, while an overall statistics smears any differences in local properties.

IV. HIGH RESOLUTION TEMPERATURE RECORDS

In order to reveal different statistical properties of daily minimum and maximum temperatures, we analyzed two records of high temporal resolution. One is from the meteorological station of the Eötvös University, Budapest, Hungary, at the campus of the Faculty of Sciences (47.47°N, 19.07°E). The other is the "Nerrigundah Catchment" [25] located 11 km north-west of Dungog, NSW, Australia (32.19°S, 151.43°E). Standard surface temperature (2 m) and radiation data of 10 min resolution were evaluated for both places covering two whole years: 2001–2002 in Budapest and 1997–1998 in Nerrigundah. Note that both locations have temperate climate.

Daily extreme temperatures are usually determined for a given calendar day (we adopted this definition), however other schemes are also used (e.g., from 7 a.m. to 7 a.m. of the next day, etc.). We show in Fig. 5 the time when daily extremes occurred for a one year period. It is clear for both places that the probability for maximum temperatures peaks ≈ 2 h after culmination, with a few exceptional days in winter of continental Hungary. The characteristic time for minimum temperature is around sunrise, however the dispersal is much stronger during the night hours with a concentration at around midnight. As a consequence, the probability distribution for intervals between extremes on consecutive days

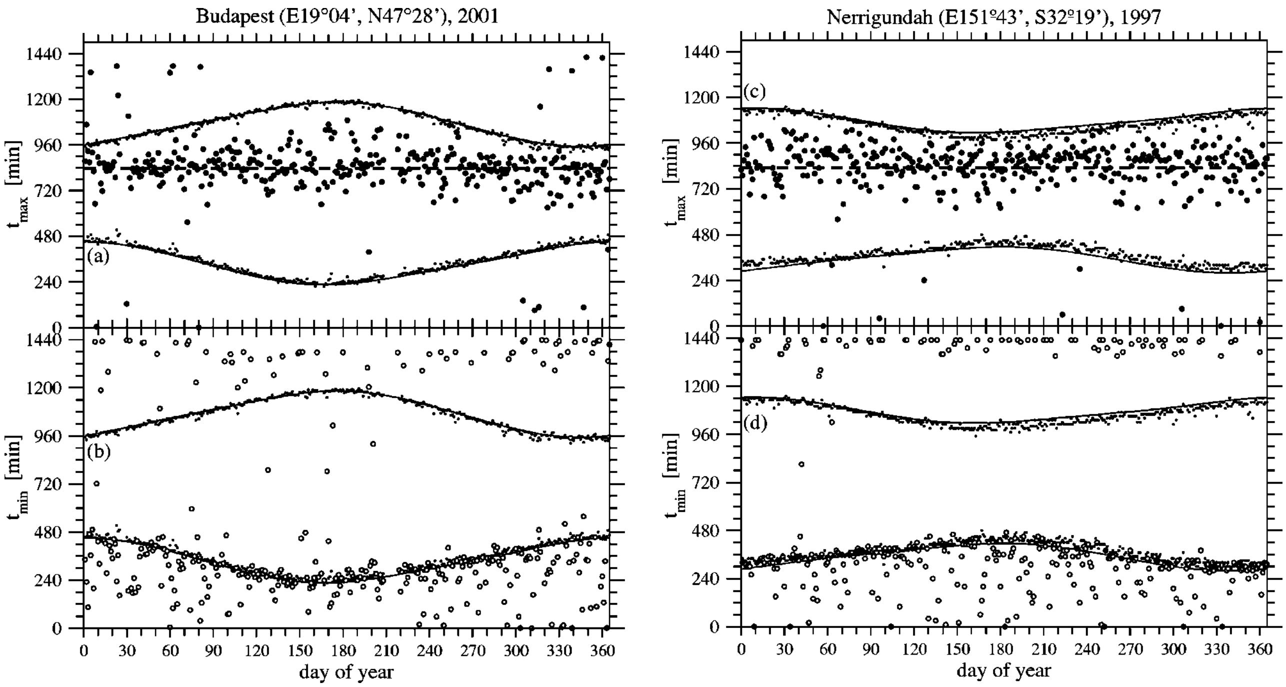

FIG. 5. Recorded time of daily extremes t_{max} (solid circles) and t_{min} (empty circles) on the given calendar day for (a,b) Budapest, and (c,d) Nerrigundah farm. Thin solid lines indicate the astronomically calculated time for sunrise and sunset, small dots around them denote the detected time by the radiometers. (Daylight-saving time is corrected.)

shows significant differences: while maxima have a single peaked histogram, minima show trimodal distributions, see Fig. 6.

We can draw the conclusion that a time series of daily maximum temperatures fulfills the condition of even sampling better than daily minima. Uneven sampling can be a significant source of error in statistical analysis [26], especially because corrections are not possible from daily data sets (the time of occurrence is simply not recorded). We performed tests on synthetic time series in order to detect the effect of uneven sampling [27]. Without the details, the result was negative: long-range persistence is a robust property which is not sensitive to the uneven sampling of type shown in Fig. 6, similarly to the case of missing whole segments [22].

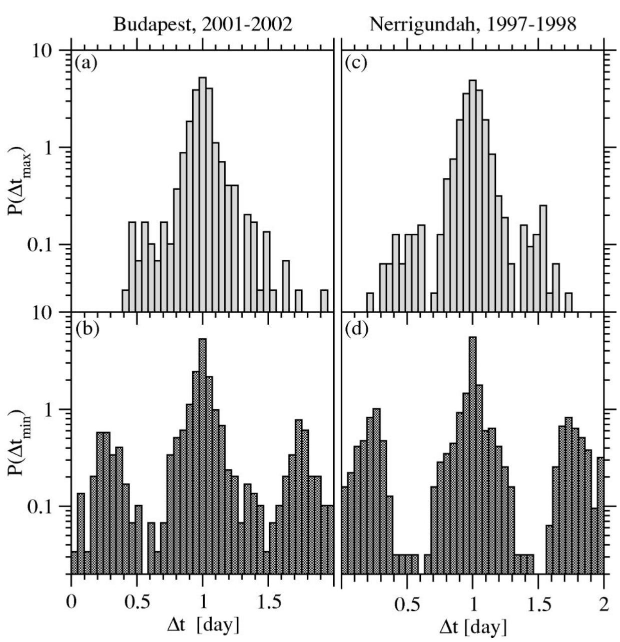

FIG. 6. Histogram for the time interval between two consecutive daily extreme values (cf. Fig. 5). (a,b) Budapest maxima and minima, and (c,d) Nerrigundah maxima and minima. Two year statistics for both stations.

As a next step, we studied more closely the characteristics of daily extreme temperatures. Visual evaluation of the records revealed that 80–100 days a year show a very regular temperature course, see Fig. 7. The weather is calm on these days, and radiation data indicate the lack of strong fluctuations in cloudiness (cloud cover itself is not excluded). Also the average temperature can be strongly different from long term mean values [Fig. 7(a)]. On such days, significant parts of the warming and cooling periods can be fitted well with exponential functions:

$$T(t) = T_w(d)\left[1-\exp\left(-\frac{t}{\tau_w(d)}\right)\right], \tag{6}$$

$$T(t) = T_c(d)\left[1+\exp\left(-\frac{t}{\tau_c(d)}\right)\right], \tag{7}$$

where the physically interesting parameters are the asymptotic warming and cooling temperatures $T_w(d)$ and $T_c(d)$, and the time constants $\tau_w(d)$ and $\tau_c(d)$ for the given day. The exponential behavior of warming is an empirical approximation only (the time dependence of irradiation, ab-

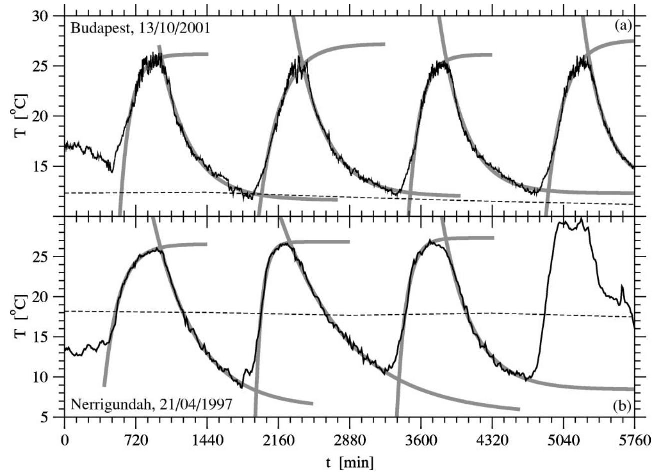

FIG. 7. Temperature records for consecutive days of calm weather for (a) Budapest and (b) Nerrigundah. Thin dashed lines indicate long term average temperatures, thick gray lines are exponential fits.

sorption, and emission complicates the physics), however it is better understood for free cooling [28].

The general statistics of time constants τ_w and τ_c is shown in Fig. 8. The important aspects for the present context are that the values and distributions are essentially the same for both stations, and there is no visible sign of an annual cycle. Note that the most probable value and the width of the histogram for the characteristic cooling time are significantly larger than that for the warming.

It is rather illuminating to examine the correlation statistics between daily extreme values and the fitted asymptotic temperatures. The asymptotic temperature can be considered as an attribute of a thermodynamic equilibrium of the lower atmosphere, where the bottom layer relaxes with unchanging boundary conditions. Of course, here we refer to local dynamic equilibrium which can be established with time dependent excitation (solar irradiation), and can be far (as it is) from a static equilibrium state. Figure 9(a) shows the scatter plot for cooling asymptotic temperature T_c and minimum temperature T_{min} for the same calendar day, and the histogram of their difference. The skewed distribution indicates that the daily minimum might be higher by 10–15 °C and

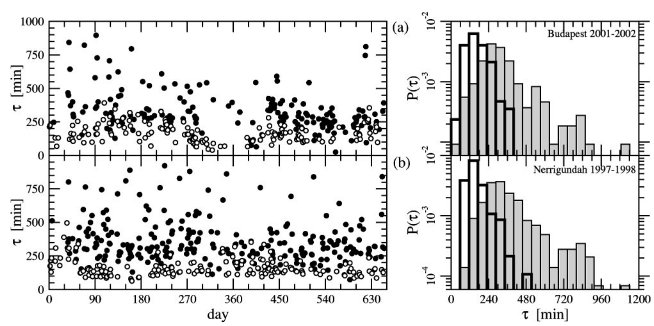

FIG. 8. Warming and cooling time constants τ_w (empty circles) and τ_c (solid circles) expressed in units of minute for (a) Budapest and (b) Nerrigundah. The appropriate histograms are plotted on the right, empty bars for warming, shaded bars for cooling.

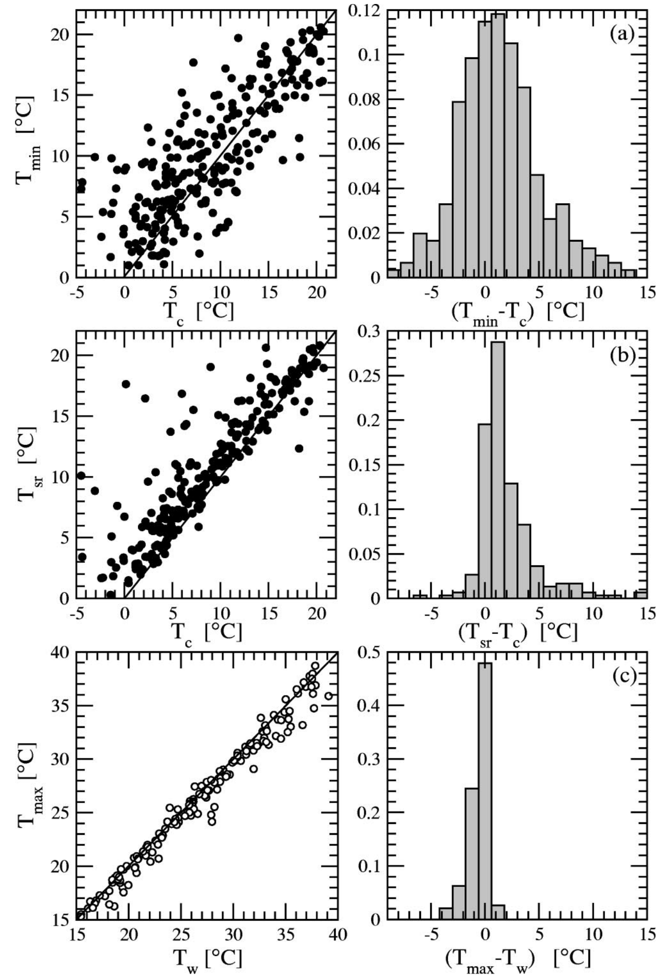

FIG. 9. Correlation statistics (a) for daily minima T_{min} and cooling asymptotic temperature for the same day T_c, (b) for the temperature at sunrise T_{sr} and T_c, (c) for daily maxima T_{max} and warming asymptotic temperature for the same day T_w. Left side: scatter plots (thin lines indicate full correlation), right side: histogram of the differences. Data for Nerrigundah are shown, the graphs are essentially identical for Budapest.

lower by 5–7 °C than the asymptotic value. The former case typically occurs at small cooling rates (large values of τ_c), where the calendar breaks the relaxation process "too early." Negative deviation is typical at general warming trends, where the daily absolute minimum is recorded before sunrise, but the asymptotic temperature is associated with the night time relaxation of the given calendar day. This is clearly demonstrated in Fig. 9(b), where T_c is compared with the local minimum temperature just before sunrise T_{sr}. Figure 9(c) shows the same statistics for warming characteristic temperatures. Since the rate constants are smaller (cf. Fig. 8), the warming process itself is much faster than cooling, thus the difference between the asymptotic and actual extreme temperatures is significantly smaller than that for cooling.

V. CONCLUSIONS

In Sec. II we reported on geographic trends of the DFA exponent over Australia. In spite of statistical deficiencies (e.g., the coverage of the continent is quite uneven), the data indicate strongly that the fluctuations are not universal. This observation is supported by the results of Tsonis *et al.* [23], where they found a very similar tendency for the whole northern hemisphere. The lack of universal exponent value does not rule out the existence of a general mechanism behind long-range temporal correlations, as illustrated in Sec. III.

The fact that daily extreme temperatures can behave differently is not new. Easterling *et al.* pointed out that diurnal temperature range (daily maximum minus daily minimum) has declined significantly over many parts of the globe in the last decades, and this is the consequence of a fast increase of daily minima [29]. Besides urbanization, this trend can be influenced by many factors such as slowly changing cloud cover, average soil moisture, surface albedo, etc. (see, e.g., Ref. [30] and references therein). It is an interesting question, how the variability (measured, e.g., by DFA) might be related with the slow trends of extreme temperature values. Since higher order DFA filters out any trend from the records, further analysis is required to reveal possible relationship between trends and correlation properties.

In Sec. IV we demonstrated that daily minimum and maximum temperatures exhibit different statistical properties in many respects, even aside from slow trends. We think that the most important concept is the evaluation of asymptotic temperatures T_w and T_c [see Eqs. (6) and (7)], which is possible only for records of high enough temporal resolution. We believe that long-memory processes in the atmosphere are reflected by slow, smooth, persistent changes in the boundary conditions, which shift the (dynamic) equilibrium of the atmosphere. Daily weather represents strong fluctuations around this potential equilibrium, therefore average quantities over appropriate time intervals are adequate characteristics of the slow changes. Nevertheless daily values reflect also long-time correlations, if they are not masked by, e.g., uncorrelated interruptions. Figure 9 illustrates that daily maximum temperatures characterize better the potential equilibrium state than daily minima for the two stations. Section III shows a mechanism, how larger amount of uncorrelated segments results in an apparently lower correlation exponent.

Of course, our results cannot prove the correctness of the concept. The distance between the Nerrigundah farm and Gunnedah [the closest meteorological station of evaluated daily records, see Fig. 2(a)] is ~200 km, which is large enough not to be comparable, and we do not have the appropriate daily data for Budapest. Nevertheless we think that the approach itself is correct: only the evaluation of high resolution records can help to understand better different scaling properties for daily extreme temperatures.

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