Heterogeneity of scaling of the observed global temperature data

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ABSTRACT

We investigated scaling properties of two datasets of the observed near-surface global temperature data anomalies: the UK Meteorological Office and the University of East Anglia Climatic Research Unit Had-CRUT4 dataset, and the NASA GISS Land-Ocean Temperature Index (LOTI) dataset. We used detrended fluctuation analysis of second order (DFA2) and wavelet-based spectral (WTS) analysis to investigate and quantify the global pattern of scaling in two datasets, and to understand better cyclic behavior as possible underlying cause of the observed forms of scaling. We found that, excluding polar and parts of subpolar regions due to their substantial data inhomogeneity, the global temperature pattern is long-range autocorrelated. Our results show a remarkable heterogeneity in the long-range dynamics of the global temperature anomalies in both datasets. This finding is in agreement with previous studies. We additionally studied the DFA2 and the WTS behavior of the local station temperature anomalies and satellite-based temperature estimates, and found that the observed diversity of global scaling can be attributed both to the intrinsic variability of data, and to the methodology-induced variations that arise from deriving the global temperature gridded data from the original local sources. We finally found differences in global temperature scaling patterns of the two datasets, and showed instances where spurious scaling is introduced in the global datasets through spatial infilling procedure, or the optimization of integrated satellite records.

1. Introduction

Global near-surface air temperature databases are standardly derived from long-term instrumental temperature measurements, and are offered for public use to document and help understanding historical and ongoing climate variations and change (Karl et al. (1993)). Of several groups that produce such databases the NASA Goddard Institute for Space Studies (GISS), the NOAA National Centers for Environmental Information (formerly the National Climatic Data Center, NCDC), and a joint effort of the UK Meteorological (Met) Office Hadley Centre and the University of East Anglia Climatic Research Unit (with the corresponding dataset dubbed Had-CRUT) are the three most prominent (Hansen et al. (2010); Morice et al. (2012); Smith et al. (2008)). Input observations to these datasets are largely drawn from the same sources: the World Meteorological Organization (WMO) and Global Climate Observation System (GCOS) initiatives provide the bulk of the land stations data (Morice et al. (2012); Jones et al. (2012)), while the International Comprehensive Ocean-Atmosphere Data Set (ICOADS), a compilation of meteorological records collected by ships and drifting and tethered buoys, is the main source of the ground ocean data (Morice et al. (2012); Freeman et al. (2017)). All the observational data are typically updated monthly (Morice et al. (2012)). Despite their common sources of observational data, the datasets largely differ in the approaches followed to handling data issues such as the incomplete spatial and temporal coverage, or non-climatic influences on measurement station environment (Hansen et al. (2010); Morice et al. (2012)). Further, methodological differences in the construction of datasets include usage or lack thereof of spatial infilling (Hansen et al. (2010)), incorporation of satellite measurements (Reynolds et al. (2002)), and estimation of near-surface air temperature above sea ice (Smith et al. (2008); Hansen et al. (2010)). Finally, all prominent global temperature datasets are given in a form of temperature anomalies, calculated against different climatological reference periods, with different resolution of spatial averaging and interpolation, that is, with different sizes of corresponding grid elements (Hansen et al. (2010); Morice et al. (2012); Smith et al. (2008)).

Comparative assessments of these datasets indicate their consistency regarding certain components of temperature variability such as, e.g., hemispheric or global trends (Hansen et al. (2010)). However, a reliable quantifica-
tion of consistency lacks the estimation of uncertainty in the long-range spatial and temporal temperature characteristics, originated by both intrinsic variability of data, and by the structural differences between the datasets. In this regard, scaling properties are known to characterize correlated randomness (Stanley (2005)) that persists over wide range of time scales. In this paper we investigate scaling properties of the two main global temperature datasets - the current versions of the HadCRUT (HadCRUT4) and of the NASA GISS Land-Ocean Temperature Index (LOTI). By calculating power-law exponents of appropriately prepared statistical functions that describe the gridded monthly data time series, we determine the existence and forms of global patterns of the observed near-surface air temperature stochastic variability, and assess the influence of structural uncertainties that arise from the choice of particular dataset preparation methodology on the quantification of long-range spatial and temporal order of the data.

The role of stochasticity in climate state and variability has been extensively studied since the initial application of present-day scaling techniques in statistical hydrology (Hurst (1951); Mandelbrot (2001)). Specifically, it was determined that observational and derived regional and global temperature data show strong natural long-term persistence. It can be described by the autocorrelation function \( C(s) \) that decays by a power-law of the separation time lag \( s \) (Tamazian et al. (2015); Carvalho et al. (2007); Tsonis et al. (1999, 2003)) in such a way that the mean correlation time for infinitely long records diverges (a criterion for a long-term persistence, or a long-range order, or a long-range memory). In this paper we presume scaling to be a sign of the existence of such long-range (correlated) order in data; for a critical discussion of this approach and alternative explanations we refer to studies referenced in this regard in Kantelhardt et al. (2006).

The existence of spatial heterogeneity in temperature long-range behavior was reported in systematic studies of persistence and trends in land station records (e.g., Bunde and Havlin (2002); Eichner et al. (2003); Govindan et al. (2003); Alvarez-Ramirez et al. (2008a); Ludescher et al. (2016)), and to a certain extent also in previous versions of the HadCRUT (that is, in HadCRUT2) gridded data (see Fraedrich and Blender (2003); Bunde et al. (2004); Fraedrich and Blender (2004)). We aim to add to this body of knowledge by extending scaling analysis to consider the global average temperatures and the corresponding spatially resolved gridded data, in order to calculate complete gridded patterns of global temperature scaling, for the two prominent datasets, and their corresponding spatially resolved data. The implications of scaling in global temperature data encompass the choice of the appropriate null-hypothesis for the statistical characterization of natural variability in the detection and attribution studies (Koutsoyiannis (2003); Zorita et al. (2008); Lennartz and Bunde (2009, 2011); Markonis and Koutsoyiannis (2013); Vavrzos et al. (2014); Tamazian et al. (2015); Ludescher et al. (2017)), the design of reliable statistical climate model alternatives (Ashkenazy et al. (2003); Tsonis and Roebber (2004); Berezn et al. (2012); Franzke et al. (2015)), along with a contribution to understanding the complexity of temperature records’ fluctuations (Mandelbrot and Wallis (1968); Stanley (2000)).

In this paper, scaling properties of global temperature data are described through the scaling (or Hurst) exponent \( \alpha \) of each temperature grid point time series. To determine \( \alpha \), we used 2nd order detrended fluctuation analysis (DFA2, see, e.g., Kantelhardt et al. (2001)), where linear trends in the data are systematically removed. We used DFA2 in combination with the wavelet transform (WT) power spectral analysis, to confirm the DFA2 results by determining the scaling exponent \( \beta \) of the wavelet power spectra (Blesić et al. (2003); Bashan et al. (2008)). In addition, we used WTS to provide us with an insight into the existence, positions and amplitudes of significant periodic or non-periodic cycles in the data (Sarvan et al. (2017); Stratimirović et al. (2018)). To this end we used Morlet wavelets of the 6th order as a wavelet basis for our analysis. The Morlet wavelets have proven to possess the optimal joint time-frequency localization (Goupillaud et al. (1984); Torrence and Compo (1998)), and can thus be effectively used to detect locations and spatial distribution of singularities in time series (Mallat and Hwang (1992); Zanchettin et al. (2008)). We calculated the scaling exponents \( \alpha \) for all the available grid point data of the two datasets, without restrictions regarding the amount of missing data. The purposes of this approach were to obtain global spatial pattern(s) of scaling, to examine its differences and similarities for two databases, to identify dissimilarities that stem from inhomogeneities due to data management (Karl et al. (1993); Peterson et al. (1998); von Storch et al. (2012)), and to test the robustness of our methods against data nonuniformity (Hu et al. (2001); Chen et al. (2002); Rust et al. (2008)). Our results may be compared with other methods of data analysis, such as the Fourier transform power spectral analysis or the calculation of the autocorrelation function, through direct dependence (Talkner and Weber (2000); Höll and Kantz (2015)), and scaling relations given bellow. Finally, our approach did not hypothesize any particular underlying physical process as a source of scaling. It can nevertheless be compared to the outputs of approaches based on different other functional forms and/or specific model assumptions, such as with the structure functions analysis based on the concept of scale invariance in turbulence (Schertzer and Lovejoy (1987, 1990); Talkner and Weber (2000); Lovejoy and Schertzer (2013); for the comprehensive assessment of links of structure function analysis to DFA please see Talkner and Weber (2000) and Kantelhardt et al. (2006).
Our paper is structured as follows: in Sec. 2, we give a brief overview of the sources of data, and of the general methodological framework of the DFA and the WTS analysis. In Sec. 3, we present the results of the usage of DFA2 and WTS to study scaling properties of the HadCRUT4 and the NASA GISS LOTI datasets. This includes our findings that concern possible sources of the observed anti-autocorrelated (with scaling exponents $\alpha < 0.5$) and highly autocorrelated (with $\alpha > 1$) behavior in some of the HadCRUT4 grid cells, and of the results of the use of DFA2 and WTS to understand the observed differences in scaling between HadCRUT4 and NASA GISS LOTI. We end our paper with a list of conclusions and a few suggestions for future work in Sec. 4.

2. Data and Methods

a. Data

We used the NASA GISS LOTI gridded monthly temperature anomalies data available on the GISS Surface Temperature Analysis (GISTEMP) web-site (GISTEMP Team (2017)). We used the LOTI data derived from the analysis that combines Extended Reconstructed Sea Surface Temperature (ERSST) version 4 (Huang et al. (2015); Liu (2012); Huang et al. (2016)) dataset with optimum interpolation (OI) of the satellite data, and with 1200 km spatial smoothing for insufficient coverage (Hansen et al. (2010)). In GISTEMP the grid boxes are of the size 2° latitude by 2° longitude. We also used the Met Office Hadley Centre observational gridded data set HadCRUT4, which provides median temperature anomalies from the 100 ensemble members in each grid box (Moricel et al. (2012)), available on the Met Office web-site (UK Met Office (2010)). In HadCRUT4 the grid boxes are of the size 5° latitude by 5° longitude. For parts of our analysis that compare results obtained on particular grid elements with those obtained using the source observational data of the same grid cell, we used land stations data provided by the Google Earth interface for HadCRUT4 land temperature dataset CRUTEM4 (Jones et al. (2012); Osborn and Jones (2014); CRUTEM4 Team (2017)), and the NCDC Global Historical Climatology Network (GHCN, version 3) land stations monthly data (Lawrimore et al. (2011); GHCN Team (2017)). To compare our results for the gridded data with marine observations, we considered the ICOADS version 2.5 time series provided by the Royal Netherlands Meteorological Institute (KNMI) Climate Explorer web-application (KNMI Team (2017)). Whenever it was possible, we used both unadjusted and adjusted land station or marine measurements, to account for the effects of data homogenization (Rust et al. (2008)). Finally, as a source of satellite temperature measurements we used the University of Alabama in Huntsville (UAH) satellite temperature analysis (Christy et al. (2003); UAH Team (2017)) in combination with the NCDC OI Sea Surface Temperature (OISST; Banzon et al. (2016); Reynolds et al. (2007); OISST Team (2017)); in UAH the grid boxes are of the size 2.5° latitude by 2.5° longitude, while the OISST dataset has a resolution of 1° latitude by 1° longitude. An overview of our data sources is given in Table 1.

Whenever the time series were given in absolute temperatures we calculated their anomalies using conventional deseasoning against the mean of the entire periods of recording for each time series, in order to correctly compare their DFA2 and WTS results with the corresponding outputs of HadCRUT4 and NASA GISS LOTI time series; in this paper we refer to such deseasoned records as the "raw data". This method of seasonal detrending had been proven appropriate for the purpose and design of our study, i.e., the assessment of (monofractal) scaling and consistency of cycles in data (Livina et al. (2011); Ludescher et al. (2011); Bunde et al. (2013)). If the original absolute temperature data were used, this would lead to a remarkable change in DFA2 results; in the range of scales of interest to this paper the seasonal trend will dominate DFA2 (and WTS) behavior in such a profound way that the estimation of scaling will be impossible and DFA2 functions will be almost undistinguishable for different observational records (Hu et al. (2001)).

b. Methodology

We used the detrended fluctuation analysis (DFA) and the wavelet transform power spectrum (WTS) approaches for data analysis.

DFA was introduced as an appropriate scaling analysis to deal with non-stationary records that contain some trends of unknown form (Peng et al. (1994)). In DFA, the procedure of detrending was devised so as to eliminate such trends. The resulting remarkable performance of this method in data analysis critically stems from this highly effective detrending solution, as shown by numerous systematic studies that investigate the effects of trends, non-stationarities and non-linearities (Hu et al. (2001); Chen et al. (2002, 2005)), as well as the effects of extreme data loss (Ma et al. (2010)) on the DFA function form, and compare DFA with other detrending methods (Xu et al. (2005); Bashan et al. (2008)) or other independent methods of data analysis (Alvarez-Ramirez et al. (2008b); Rodriguez et al. (2014)). Recently, a new mathematical insight was provided that further illuminates how DFA operates on non-stationary data series with non-stationarity due to their intrinsic dynamics (Höll et al. (2016)).

We applied the version of DFA (Peng et al. (1994)) that utilizes the detrending procedure on a set of overlapping segments (Buldyrev et al. (1995)) of a time series of duration (number of data points) $N$, which is described in detail in Blesic et al. (1999) and Milošević et al. (2002). In this
version of DFA, any time series $A(k)$ ($k = 1 \ldots N$) is firstly transformed into a series of its partial (or cumulative) sums
\[ y(l) = \sum_{k=1}^{l} [A(k) - A_{ave}], \]
where $A_{ave} = \frac{1}{N} \sum_{k=1}^{N} A(k)$. For any given overlapping segment of length $n$ of $y(l)$, $y_{n,i}(l)$ ($i = 1 \ldots N-n+1$), the procedure of detrending is applied: the local trend is calculated through a polynomial least-squares fit (Kantelhardt et al. (2001)) and subtracted from $y_{n,i}(l)$. The polynomial degree that defines the local trend represents the DFA order; in our case it is two, that is, we used a quadratic function. Finally, the average of variances about the local trend obtained over all segments is calculated (Peng et al. (1994)), thereby producing the detrended fluctuation function:
\[ F(n) = \sqrt{\frac{1}{N-n+1} \sum_{i=1}^{N-n+1} \sum_{j=1}^{n} (y_{n,i}(l))^2}. \] (1)

The function $F(n)$ increases with the segment length $n$ (Blesic et al. (1999)). If (any) $A(k)$ is short-range auto-correlated, or has no correlations at all, $F(n)$ behaves as $n^{\alpha/2}$ (Peng et al. (1994)). Differently, for data with power-law long-range autocorrelations the expectation is that $F(n) \sim n^\gamma$, with $\alpha \neq 0.5$. Namely, we call the data long-range autocorrelated, or long-term persistent (LTP), when the corresponding autocorrelation function $C(s)$ decays by a power law $C(s) \sim s^{-\gamma}$, for $s > 0$ and $N \rightarrow \infty$. If this is the case, $\gamma$ represents the correlation exponent that quantifies the nature and the level of autocorrelations in the record; for stationary cases $\gamma$ lies in the range $0 < \gamma < 1$. Correlations are generally termed “long-range” when the mean correlation time, defined as $T = \int_{0}^{\infty} C(t)dt$ diverges (Höll and Kantz (2015)) and thus can not be used to define the characteristic time scale of autocorrelations. It can also be shown that, in this case, the Fourier power spectral density decreases as a power law as well, with $E_F(\omega) \sim \omega^{-\hat{\beta}}$, and the exponent $\hat{\beta}$ in the range $-1 < \hat{\beta} < 1$ (Peng et al. (1993)). This bounds $\alpha$ to a range $0 < \alpha < 1$ for stationary records, where $0.5 < \alpha < 1$ indicates persistence in the record. Instances when $\alpha \geq 1$ imply the existence of intrinsic non-stationarities in the data (Höll et al. (2016)); in this case DFA functions exhibit crossovers, while $\alpha \geq 1$ may mean that the underlying process is of a composite nature (Höll and Kantz (2015)), or that there exists an imbalance between different noise inputs (Peng et al. (1995)). Finally, $\alpha = 1.5$ indicates Brown noise, the integration of white noise.

The WT was introduced in order to circumvent the uncertainty principle problem in classical signal analysis (Stratimirović et al. (2018)) and achieve better signal localization in both time and frequency than classical Fourier transform approaches (Morlet (1983); Grossmann and Morlet (1984)). In WT, the size of an examination window (equivalent to the size of a sliding segment in DFA) is adjusted to the frequency analyzed. In this way an adequate time resolution for high frequencies and a good frequency resolution for low frequencies is achieved in a single transform (Bracić and Stefanovska (1998)).

The continuous WT of a discrete sequence $A(k)$, as defined in Morlet (1983) and Grossmann and Morlet (1984), and described in detail in Stratimirović et al. (2001) and Milošević et al. (2002), is the convolution of $A(k)$ with wavelet functions $\psi_{a,b}(k)$: $W(a, b) = \sum_{k=0}^{N-1} A(k) \psi_{a,b}(k)$. Here, $a$ and $b$ are the scale and translation-in-time (coordinate) parameters, and the asterisk stands for complex conjugate. In order to obtain the kind of results comparable with those of the DFA method, we calculated the wavelet scalograms (mean wavelet power spectra) $E_W(a)$, which are defined as $E_W(a) = \int W^2(a,b)db$. The scalogram $E_W(a)$ can be related (Perrier et al. (1995)) to the corresponding Fourier power spectrum $E_F(\omega)$ via the formula
\[ E_W(a) = \int E_F(\omega) |\hat{\psi}(a\omega)|^2 d\omega, \]
where the hat designates the Fourier transform, while $E_F(\omega) = |\hat{A}(\omega)|^2$. It stems from Eq.2 that, if any of the

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**Table 1.** Monthly data sources, with major parameters, and number of data points $N$ used for scaling analysis.

<table>
<thead>
<tr>
<th>Source and version</th>
<th>Spatial resolution</th>
<th>Anomalies calculation and spatial infilling (does not include the treatment of sea ice)</th>
<th>Start year</th>
<th>$N$</th>
</tr>
</thead>
<tbody>
<tr>
<td>HadCRUT4</td>
<td>5° by 5°</td>
<td>average of observational data (with correction for errors as median of 100 realizations), weighted for all the non-missing grid-boxes in each hemisphere, and averaged over hemispheres</td>
<td>1850</td>
<td>1820</td>
</tr>
<tr>
<td>CRUTEM4</td>
<td>5° by 5°</td>
<td>average of observational data (with correction for errors), weighted in the same manner as HadCRUT4</td>
<td>1850</td>
<td>various</td>
</tr>
<tr>
<td>GISS (GISTEMP) LOTI</td>
<td>2° by 2°</td>
<td>average of observational data (with adjustment for errors), with addition of weighted averages of stations records in the radius of 1200 km (alternatively 250 km) from the grid cell center, weighted over zones by the zones full area</td>
<td>1880</td>
<td>1640</td>
</tr>
<tr>
<td>GHCNv3</td>
<td>–</td>
<td>unadjusted and adjusted (for non-climatic influences) land stations data</td>
<td>1701</td>
<td>various</td>
</tr>
<tr>
<td>ICOADSv2.5</td>
<td>–</td>
<td>quality controlled individual marine observations</td>
<td>1662</td>
<td>various</td>
</tr>
<tr>
<td>OISSTv2</td>
<td>1° by 1°</td>
<td>optimum interpolation (OI) of sea surface and satellite records</td>
<td>1981</td>
<td>420</td>
</tr>
<tr>
<td>UAHv6 (TLT)</td>
<td>2.5° by 2.5°</td>
<td>quadratic approximation to the average control radiosonde data, with removed non-climatic influences and inter-satellite differences</td>
<td>1979</td>
<td>456</td>
</tr>
</tbody>
</table>
two spectra - \(E_W(\alpha)\) or \(E_F(\alpha)\) - exhibit power-law behavior, then the other will be of the power-law type as well, with the same power-law exponent \(\beta\) (Stratimirović et al. (2001)). The meaning of the wavelet scalegram is the same as that of the classical Fourier spectrum: it calculates the contribution to the signal energy along the scale of \(a\).

In this paper, we found it convenient to use the standard set of Morlet wavelet functions as a wavelet basis for our analysis (Morlet (1983); Grossmann and Morlet (1984)).

We calculated DFA2ff fluctuation functions (DFA2ff) and WT power spectra (WTS) for the temperature anomalies data series, and plotted them on double logarithmic time/scale axes so that the exponents \(\alpha\) or \(\beta\) are estimated by linear fit. We took into consideration only the values of DFA2ff between the minimum time scale of \(n = 5\) and the statistically meaningful maximum time scale of \(n = N/5\) that we decided to use following recommendations in Hu et al. (2001), Kantelhardt et al. (2001), Chen et al. (2002), Bashan et al. (2008), and Ludescher et al. (2017). Similarly, we calculated WTS between the time scales of \(n = 1\) and \(n = N/5\), following the argument that the upper meaningful time scale for the use of Morlet wavelets can be even higher than \(N/5\) (Bračić and Stefanovska (1998)). In search for cycles in WTS, however, we looked for characteristic peaks (i.e., local maxima) just within the limits of maximum meaningful scale set at \(n = N/10\) (Koscielny-Bunde et al. (2006)). To ensure that the peaks that we obtained in such a way are not artefacts of the WT design, we additionally performed a test of statistical significance for each peak (Stratimirović et al. (2018)), using the tool kit described in Torrence and Compo (1998) and ready-to-use software available online at the web-site of the University of Colorado in Boulder (UC Boulder Team (2017)). The significance of each peak was determined by comparing its amplitude against the background global wavelet spectrum for the corresponding timescale. This choice was guided by the consideration that the time series of temperature anomalies describe the evolution of a complex system that results from interactions of many constituents acting on different time scales (Liu (2012); Zanchettin (2017)), and are thus mixtures of noise components from different inputs involved in the process (Stratimirović et al. (2018)).

3. Results

We calculated the DFA2ff and the WTS and their corresponding scaling exponents \(\alpha\) and \(\beta\) for the HadCRUT4 and NASA GISS LOTI global-average time series of temperature anomalies, and the DFA2 exponents \(\alpha\) for each grid point time series, for the two temperature anomaly products. In Figure 1 we present the combined DFA2-WTS results for the global-average HadCRUT4 and NASA GISS LOTI series, together with their raw data; here, and hereafter, DF2-WTS represents abbreviated notation for the results independently derived from DFA2 and WTS. In Figure 1, the DFA2ff and the WTS are depicted in the form \(F(n)\) versus \(n\), and \(\sqrt{E_W(n)}\) versus \(n\), so as to provide a simple visual comparison of two methods, given the scaling relation \(\alpha = (\beta + 1)/2\).

For the HadCRUT4 global-average series, we obtained \(\alpha = 0.92 \pm 0.04\), and found prominent annual, two interannual and a near-decadal cycle in the WTS spectrum. The NASA GISS LOTI time series yields \(\alpha = 0.97 \pm 0.04\) and its WTS indicates a prominent annual cycle as well as strong interannual and decadal variability. The calculated values of the scaling exponents \(\alpha\) and \(\beta\) align, for both data series, within the range of standard deviation of \(\alpha\) that depends on the time series length \(N\) (Bashan et al. (2008)), in agreement with previous findings (Markonis and Koutsouyanni (2013); Lennartz and Bunde (2011)). In what follows we separately illustrate the results for the grid points time series for the two datasets, then explore their differences.

a. Global pattern of scaling: HadCRUT4

Figure 2 shows the global scaling pattern of the time series of HadCRUT4 gridded temperature anomalies. Depicted are values of the scaling exponent \(\alpha\) for the time series of each grid point on the 5° by 5° grid, together with the latitudinal averages of the exponent \(\alpha\). Long-range correlated behavior is found in all of the grid points belonging to the ocean regions, and in nearly all grid points on land (in 27 land grid cells we found \(0.45 \leq \alpha \leq 0.5\)). There is a land-ocean contrast in persistence, with marine data that feature a substantially more pronounced LTP than land data, a result that agrees with previous findings based on individual station data (Bunde and Havlin (2002)), and the partial assessment of the HadCRUT2 grid.
Our results additionally reveal the non-uniformity of scaling within ocean as well as land data: this is how, for example, there is a region of higher-than-average LTP in the tropical land data, possibly following the distribution of rain forests, or a region of lower-than-average LTP that differentiates the Indian ocean from other basins (e.g., Zanchettin et al. (2013)) that can be a signature of the South Equatorial current (Rybski et al. (2008)), or instances of higher-than-average LTP in various ocean basins that is arguably a signature of currents (in upwelling regions, or at the Subpolar Gyre in the North Atlantic Ocean). In order to enable a detailed examination of the heterogeneity of HadCRUT4 global temperature scaling in the Supplementary material we provide two additional maps of the global scaling pattern, with the interval thresholds of mapping set at 1/2 and at 1/4 of the interval presented in Figure 2.

Figure 2 also shows latitudinal averages of the DFA2 exponent \( \alpha \), calculated along the 36 latitude rows of the HadCRUT4 dataset. It presents a weak latitude dependence of \( \alpha \), with lower LTP in high latitudes; this pattern seems to follow the global distribution of land, and is probably somewhat affected by the strong influence of El Niño-Southern Oscillation (ENSO) teleconnections in the mid-latitudes (Graf and Zanchettin (2012)). The global averages of the scaling exponent \( \alpha \) - the normal average, calculated as the average of all the DFA2 exponents of all the grid cells (when it is \( \alpha_{\text{ave}}^{hcn} = 0.64 \pm 0.04 \), and the weighted average, averaged according to the grid cell areas (with weights equal to the cosines of the central latitudes of each grid box (UK Met Office (2010)), which yields \( \alpha_{\text{ave}}^{hcn} = 0.72 \pm 0.04 \), are different from the value of \( \alpha \) that we obtained for the global time series, \( \alpha = 0.92 \pm 0.04 \) (shown in Fig 1). This result may be explained if we keep in mind the dataset construction methodology. Namely, the HadCRUT4 global temperature series (and similarly NASA GISS LOTI; see Table 1) is constructed as the weighted average of all the non-missing grid-box anomalies, which are themselves (non-weighted, except for the grid cells composed of a combination of land and marine data) spatial averages of instrumental records enclosed in each grid box. The process of averaging merges (adds) values of monthly data points from different records, and thus superposes their different scaling and different cyclic amplitudes and distribution, producing a global temperature signal that yields the scaling properties of all the averaged data, together with the influence of all their cycles combined. The DFA2-WTS analysis of such a signal will naturally register all these influences. A similar combination of signals was studied in the systematic assessment of effects of non-stationarities on DFA in Chen et al. (2002), where different artificially generated time series with different scaling exponents \( \alpha \) were used to analyze properties of signals comprised of segments of these time series. The study reported that "the behavior of \( F(n)/n \) for a non-stationary signal comprised of mixed segments with different correlations is dominated by the segments exhibiting higher positive correlations even in the case when their relative fraction in the signal is small"; at that time the authors found this observation to be pertinent to real physiological records, and to be true even in cases when signals of high positive correlations comprise only 10% of the entire time series. In the Supplementary material we assessed this dominance for the HadCRUT4 temperature data, in relation to the theoretical superposition rule provided by Chen et al. (2002), and found that the effect described in Chen et al. (2002) agrees well with the averages of individual grid cell or observational record DFA2 functions, but that the dominance of the high LTP time series is even more pronounced in DFA2 functions of time series that were made as averages of individual grid cell or observational records first. In other words, even if signals with high LTP are not dominant by appearance in the global temperature pattern (which is evident from the values of \( \alpha_{\text{ave}}^{hcn} \) and \( \alpha_{\text{ave}}^{hcn} \)), and even if they may not significantly affect the local scaling (for the HadCRUT4 global scaling pattern is heterogeneous), they will have a significant relative influence on regional and global temperature scaling. Owing to the fact that both analysis products weight the temperature anomalies of grid cells by the cell’s full area, this is probably especially true for the dominance exhibited by the high LTP of grid cell data along the mid-latitudes. Figure 3 demonstrates this effect in the case of the DFA2-WTS functions for the HadCRUT4 averaged data for the Northern Hemisphere, Southern Hemisphere and the Tropics. It is obvious from Figure 3 that global
HadCRUT scaling follows (or is dominated by) the Southern Hemisphere scaling that is, in turn, likely largely influenced by the scaling at the Tropics.

In order to understand how the obtained results are affected by the data loss in regions where large amounts of source data are missing or were removed due to artifacts in the observational records (Fraedrich and Blender (2003)), or underwent a considerable adjustment due to inhomogeneous observations (Menne and Williams (2009); Alexandersson (1986)), we compared the DFA2ff and WTS behavior of the raw (unadjusted) and the adjusted data for several such land stations. Owing to the large amount of data, we could not investigate these effects for all records; we made a choice to focus our analysis on land stations that are the sole source, or one of the few sources of observations available in the considered grid cell. Our results, shown in Figure 4 for two illustrative examples, demonstrate that in such cases the DFA2 exponents for the adjusted data in the gridded dataset can be slightly or even substantially smaller than for the raw data. The corresponding WTS reveals that this is probably due to the modulation of the annual cycle, but also to strong dampening of interannual and decadal fluctuations in the adjusted data. Artificial reduction of LTP by data adjustment seems to be a general feature. The opposite behavior, that is, an increase of LTP by data adjustment as shown in Figure 5, only occurs in several polar or subpolar stations. There, systematic lack of data for entire seasons yields DFA2 exponents of the adjusted series that are slightly higher than those of the corresponding raw series, probably as a result of superposition of seasonality to the data. These findings indicate that the true DFA2 exponents for a largely predominant part of the HadCRUT4 grid where there is large percentage of missing values (Fraedrich and Blender (2003)) are likely higher than those estimated from the actual gridded data and illustrated in Figure 2. Our conclusion about a likely underestimation of the DFA2 exponent is in line with previous findings on effects of homogenization (Rust et al. (2008)) on artificial data. The results also suggest that, excluding polar and parts of subpolar regions for substantial data inhomogeneity, the HadCRUT4 global temperature is long-range correlated, that is, all the gridded DFA2 exponents are likely equal or higher than 0.5.

Finally, we inspected the DFA2ff that have scaling exponents larger than 1, to determine whether they display crossovers and thus the existence of intrinsic non-stationarities (Höll et al. (2016)) that should then be explored and understood further. None of the HadCRUT4 grid points with $\alpha > 1$ has a crossover in DFA2 behavior. The comparison with corresponding WTS, provided in Figure 6, shows that the DFA2-WTS slopes are this large probably due to the strong interannual and multi-decadal variability in their underlying data series that in the time range of statistical significance of our results may contribute to a slight overestimation of the scaling exponent $\alpha$. This result seems to follow up on the existent researches that investigate scaling of instrumental and proxy records of global temperature on much larger time scales. In particular, Lovejoy and Schertzer (2013) and Markonis and Koutsoyiannis (2013) indicate that probably there exist no prominent source of non-stationarity that would
change the scaling regime and produce crossovers in scaling behavior in the range of the instrumental data that we are interested in (up to one decade). Due to the limited range of statistically meaningful scales for instrumental records we were not able to further verify whether the scaling depicted in Figure 6 is a part of the underlying very long-term persistent (Rybski et al. (2008); Markonis and Koutsoyiannis (2013)) or anti-persistent (Carvalho et al. (2007); Lovejoy and Schertzer (2013); Luo et al. (2015)) order.

**b. Global pattern of scaling: NASA GISS LOTI**

Figure 7 shows the DFA2 global pattern for the NASA GISS LOTI 2° by 2° gridded time series, together with latitudinal averages over 90 GISS latitudes, which produce the normal average over all grid cells of $\alpha_{\text{giss}} = 0.74 \pm 0.04$ and the weighted average of $\alpha_{\text{gissw}} = 0.81 \pm 0.04$. Additional maps, created with lower interval thresholds, are provided in the Supplementary material. Visual comparison between Figure 2 and Figure 7 suggests that the NASA GISS LOTI and the HadCRUT4 data display a similar global pattern of scaling. There are, however, noticeable differences between both datasets: NASA GISS data display much more homogeneity in scaling within land and within ocean regions, with higher $\alpha$ values than HadCRUT4 over the ocean, and lower $\alpha$ values over the land. An estimate of distribution and the range of differences in values of $\alpha$ between the two datasets is given in the Supplementary Figure S3. Over the ocean, particularly high values of the DFA2 exponent, exceeding $\alpha = 1$, are identified in key regions of oceanic and coupled atmosphere-ocean variability, such as ENSO in the equatorial Pacific and at the sea-ice edge south of Spitsbergen. In contrast with the HadCRUT4 dataset where the Indian Ocean emerges as a peculiar oceanic region with low DFA2 exponents, the NASA GISS dataset yields high DFA2 exponent values especially west of the Maritime Continent. In what follows we will try to evaluate the dissimilarity in dataset construction methodologies as a source for the obtained dataset dissimilarity in regional scaling.

**Fig. 5.** Two examples of the DFA2ff (upper row) and WTS (lower row) calculated for the raw (unadjusted) and the adjusted temperature HadCRUT4 records of polar (first column) or subpolar (second column) stations that systematically miss data for entire seasons. In DFA2ff graphs the values of scaling exponents are given for both raw data ($\alpha_R$) and adjusted data ($\alpha_A$). In WTS graphs dotted vertical lines at $t = 6$ months and $t = 12$ months are given as visual guides. The coordinates indicating locations of land stations are given in graph legends.

**Fig. 6.** Examples of the calculated DFA2ff (solid lines) and WTS (filled circles) functions for the grid points in the HadCRUT4 dataset that have scaling exponents $\alpha > 1$. Vertical lines at $t = 45$ months, $t = 70$ months, and $t = 110$ months are given as visual guides.

**Fig. 7.** Main graph: DFA2 exponents $\alpha$ calculated for all available grid point time series of temperature anomalies in the NASA GISS LOTI dataset. Values of $0 < \alpha < 0.45$ belong to grid boxes with missing data. Right-side graph: Latitudinal averages of $\alpha$, calculated along the 90 latitude rows of the GISS dataset (y-axis grid lines are inserted as visual guides).
c. Understanding differences in scaling between HadCRUT4 and NASA GISS LOTI

1) LAND: EFFECTS OF THE 1200 KM RULE

Here HadCRUT4 - NASA GISS LOTI differences in values of scaling over the land are assessed accounting for the different approaches employed to solve the problem of incomplete spatial coverage in their construction. The HadCRUT4 does not employ any form of spatial infilling and, as a result, grid-box anomalies can readily be traced back to observational records (Morice et al. (2012)). The NASA GISS LOTI, instead, interpolates among station measurements, and extrapolates anomalies as far as 1200 km into regions without measurement stations (Hansen et al. (2010)). To probe whether the spatial infilling that is employed in the construction of the NASA GISS dataset determines the observed difference in scaling over land between NASA GISS and HadCRUT4, we compared the average DFA2ff and WTS of the raw adjusted station records that contribute to a HadCRUT4 grid point, with the DFA2-WTS HadCRUT4 (adjusted) result and the NASA GISS LOTI DFA2-WTS results within the corresponding grid point. We repeated this procedure for several sparsely filled (in terms of number of recording stations) and several densely populated grid points. Examples of our findings are given in Figure 8. Our results show that in sparsely filled grid cells the procedure of spatial interpolation of stations data, which is the only data processing performed in the HadCRUT4 dataset, lowers the scaling exponent $\alpha$ due to the modulation of the interannual and multidecadal variability, and to the flattening of noise at scales higher than annual. This finding is not universal for all spatially averaged HadCRUT4 data, for it depends on the relative influence of the high LTP records present within the considered grid box. In NASA GISS LOTI, the additional procedure of spatial infilling within a 1200 km radius from the selected grid point increases this effect (that is, it further decreases the value of $\alpha$; see left panels in Figure 8). Moreover, in the case that we present in Figure 8, the surrounding land grid points have significantly different scaling exponents, so that the process of extrapolation as far as 1200 km integrates spurious correlations that are entirely location-related (that is, dependent on the scaling of the nearest neighbor grid cells). For this reason, changes in the values of $\alpha$ over land introduced by the 1200 km rule in sparsely filled grid boxes cannot be viewed or corrected as for the systematic bias. Finally, the observed discrepancy between HadCRUT4 and NASA GISS LOTI scaling does not appear at grid points sufficiently populated with recording stations (see example in the right panels of Figure 8).

2) OCEAN: EFFECTS OF INCLUSION OF SATELLITE DATA

NASA GISS LOTI constructs ocean data (Hansen et al. (2010)) as an integration of the Met Office Hadley Centre analysis of SSTs (HadISST1; the sole basis of HadCRUT4 ocean data (Rayner (2003))) for the 1880-1981 period, where measurements are ship-based, and satellite SST measurements (OISST.v2, Reynolds et al. (2007)) from 1982 to the present. Satellite measurements in the NASA GISS dataset are additionally calibrated with the help of ship and buoy data (Hansen et al. (2010)). To understand how this methodological difference affects scaling over ocean regions in both datasets, we calculated and compared DFA2ff and WTS of several HadCRUT4 marine grid points with the matching average (within the same HadCRUT4 grid cell) NASA GISS LOTI, average OISST.v2, and an average UAH satellite temperature for the lower troposphere (TLT) scaling. An example of the obtained findings is given in Figure 9, showing that the TLT UAH data scale as white noise (with $\alpha \approx 0.5$ and flat $\beta \approx 0$ WTS). It seems thus that the optimization procedure employed in the construction of OISST.v2 rises the DFA2-WTS slopes of the NASA GISS data, leading to the higher NASA GISS LOTI scaling. From the WTS given in Figure 9 it is apparent that this effect is most prominent in the range of scales of up to one year, which is very likely the result of the superimposed seasonality on the marine satellite record. This result was robust for all the grid points that we probed.

4. Discussion and Conclusions

We used detrended fluctuation analysis of 2nd order (DFA2) and wavelet-based spectral (WTS) analysis to investigate and quantify the global pattern of scaling in major datasets of observed near-surface air temperature
anomalies, and to understand better cyclic behavior as possible underlying cause of the observed long-term scaling behavior. Both methods allow to overcome problems related to non-linearity and partially non-stationarity of natural data series. We focused our analysis on two prominent sources of global temperature data, namely the UK Meteorological Office HadCRUT4 and the NASA GISS LOTI gridded historical records. Our approach allowed us to characterize the global pattern of temperature scaling, and to investigate the relevance and the extent of possible influences of real or artificial (i.e., originated by data processing) cycles upon global scaling. In particular, we investigated how DFA2ff and WTS can be affected by data processing compensating for the issue of inhomogeneity of data linked to the scarcity of records or to the changes of data recording practices. Finally, we studied the possible structural sources of dissimilarities in global pattern of scaling that we found to exist between the HadCRUT4 and NASA GISS LOTI datasets.

We found that the global temperature pattern is likely long-range autocorrelated except for polar and parts of subpolar regions, where, however, data inhomogeneity is substantial. We confirmed the existence of a land-ocean contrast in persistence (Bunde and Havlin (2002); Fraedrich and Blender (2003)), with marine data showing appreciably a more pronounced long-range persistence than land data. Four prominent cyclic influences, or characteristic times of underlying processes, emerged in the time range of analysis of our data. They appear at periods of 12 months, of around 40 months, 72 months and 110 months. The first two cycles that we found in our data can be attributed to the seasonal cycle and probably to the influence of the leading ENSO eigenmode (Penland and Matrosova (2006); Compo and Sardeshmukh (2010)) on sea-surface and land temperatures. The other two characteristic times are difficult to attribute to any individual or canonical source of climate variability. We refer to researches showing that the period of approximately 6 years can be related to the variance of ENSO indices such as Niño-3.4 SSTs (Penland and Matrosova (2006)) or to the first harmonics of decadal variabilities (Zanchettin et al. (2013)), while the near-decadal period of 110 months can emerge as a response to a non-periodic strong events of volcanic eruptions (Rypdal (2012); Lovejoy and Varotsos (2016)), or as a reflection of decadal climate variability originated either by internal processes (Liu (2012)) or forced by external natural factors (Zanchettin (2017)).

We found that the spatial average of scaling of the global gridded temperatures is significantly lower than the scaling of the spatially averaged global temperature time series, and argued that this is an effect of disproportionate influence of the high LTP series, particularly those in the mid-latitudes, on regional, hemispheric and global averages. We showed that the global temperature scaling is in this way dominated by the scaling of Southern Hemisphere, which in turn is possibly significantly determined by the scaling in the Tropics. This effect explains why our values of DFA2 exponents averaged along parallels, particularly along the mid-latitudes, differ from the corresponding averages calculated for the global coupled general circulation models in Rybski et al. (2008). Finally, these observations may indicate that the spatial resolution of global temperature products can affect their local (individual grid cells) and global scaling behaviors, and that the spatial scaling may be important for understanding the dynamics underlying the observed climate variability. There is probably a need in climatically diverse regions for a more detailed sampling of the different areas (in both datasets), in order to account for their different scaling regimes in the regional estimate and to accurately determine regional dynamics.

Our results unraveled the non-uniformity of scaling within ocean or land data, and the pronounced differences of such non-uniformity in the two datasets. Our findings suggest that the observed non-uniformity of scaling can reflect a number of different natural (Fraedrich and Blender (2003)), as well as methodological causes, whose individual contribution is difficult to disentangle. We found that, for the still predominant part of the analyzed datasets affected by a large percentage of missing values, the real values of the scaling exponents are likely higher than those calculated. This result is in accordance with assessments of artificial data with similar properties (Rust et al. (2008)). We found instances of amplification of cyclic influence or even introduction of new cycles, sometimes coupled with the reduction of noise, in both datasets and due to the homogenization and optimization of the raw (unadjusted) temperature time series; these effects are probably more pronounced in cases of corrections due to the actual data loss (Chen et al. (2002); Ma et al. (2010)). Since there is no apparent universal solution to this problem, we avoid conclusively asserting the
exact nature of the dynamics underlying the temperature time series for such locations.

We also assessed structural uncertainties that arise from methodological choices made in the two temperature analysis products. We showed instances where spurious scaling is introduced in the NASA GISS dataset through spatial infilling procedure, or where reinforcement of the annual cycle is introduced due to the optimization of integrated satellite records. This highlights once more the need to consult in detail how data are prepared before assessing climate dynamics based on data analysis (von Storch et al. (2012)). Nevertheless, having in mind the stochastic nature of climate (Hasselmann (1976); Franzke et al. (2012); Watkins (2017)) and the current lack of an effective model capable of capturing long-range interactions between large number of interacting parts that would mimic LTP as an output from various climate systems (Ludescher et al. (2017)), the observed global temperature pattern of scaling can serve as a non-trivial test (Monetti et al. (2003)) for dynamic properties of current climate models.

Our results do not settle the debate about nature and origins of scaling properties of temperature, or of the observed natural non-uniformity of scaling (Levine and McPhaden (2016); Markonis and Koutsoyiannis (2013); Bunde and Lennartz (2012); Rypdal (2012); Frädrich et al. (2004); Stanley (1999); Press (1978)). Instead, they point to the heterogeneity of scaling as an important area of further investigation in this context. This seems to be crucial to progress in our understanding of the critical problem of detection and attribution of trends and other climate change evidences (Climate Dialogue (2014); Zanchettin (2017)). Specifically, if we assume that the observed temperature evolution, similar for both datasets (IPCC (2013), Fig. 2.20, p. 193), is a realization of a long-term autocorrelated process, then the appropriate statistical approaches and underlying theories must be applied to the detection problem. Current analytical approach and numerical estimations (Lennartz and Bunde (2009, 2011)) indicate the DFA2 scaling exponent α, along with the observed linear trend and the standard deviation around the data regression line, to be an important quantity to estimate anthropogenic trends. The heterogeneous scaling of global temperature reported in our study, and especially the presented evidence of weakly correlated or even random (with α ≈ 0.5) fluctuations instances in gridded temperature data, fosters further investigation.

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