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Time Correlation Laws Inferred from Climatic Records: Long-Range Persistence and Alternative Paradigms

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1. Introduction

Observational time series of climatic variables exhibit substantial changeability on spatial and temporal scales over many orders of magnitude. In statistical terms, this implies a continuous variance distribution involving all resolvable time scales (frequencies), starting from those comparable with the age of the Earth.

A correct causal interpretation of such a variability is very difficult even in the context of a cognitive approach (e.g., von Storch, 2001) to the problem.

Cognitive models are minimum complexity models aiming at the scientific understanding of the most relevant processes occurring at any given temporal and spatial scale. Although generally they cannot be useful for management decisions straightforwardly, their role is fundamental especially for understanding the internal climatic variability that cannot be passively related to external forcing factors. The concept of stochastic process is essential in this framework, since it synthesizes collective behaviours which contribute as a whole to the overall dynamics. As stochastic processes are the macroscopic result of many degrees of freedom, the characterization of their correlation properties across different scales through the analysis of observational data is a problem of statistical inference and their modelling is usually a mechanical-statistical problem.

Maybe, the most famous early effort aiming to summarize the climate variance distribution among different frequencies, which is commonly referred as climate spectrum, is the ideal sketch proposed by Mitchell (1976) (see Fig. 1).

All the features of this spectrum that deviate from the flat behaviour typical of white noise (pure random process) deserve dynamical interpretation in order to understand climate. Within the traditional picture of the climate dynamics, the variance distribution among different temporal scales is seen as the superposition of oscillations generated by astronomical cycles (spectral spikes), quasi-periodic or aperiodic fluctuations with a preferred scale (broad spectral peaks), and internal stochastic processes whose temporal correlation decays according to characteristic time scales. These last are responsible for all the continuous broad-band deviations of the spectrum from flatness. Within this picture, the variance accumulations that do not appear in the form of peaks and spikes, such as that we

can observe in-between the red vertical lines of Fig. 1 by scanning the figure from the short to the long periods, are due to the superposition of stochastic processes with different scales. This "redness" (optical analogy: dominance of low frequencies) would reflect the thermal inertia of slow climatic subsystems, such as ocean and cryosphere, and would be the result of a progressive addition of variance "shelves" (Mitchell, 1976) generated by ever slower scale-dependent processes. Hasselmann (1976) proposed an interesting interpretation of this redness by assuming that the heat-storage capacity of "slow" Earth's sub-systems act to integrate random "fast" disturbances in a dynamical context that is therefore characterized by separation between short and long scales. As an example, ocean would act as a long term integrator of the meteorological atmospheric forcing (white noise on climatic scales) thus providing "memory" to the atmosphere-ocean system in the form of non zero correlation among different scales, that is redness. The resulting simplest paradigm for this integration is Brownian motion (random walk) that is a non-stationary scale free process whose variance increases linearly with scale (Mandelbrot & van Ness, 1968). Such an ideal motion is able to produce random trends of any length but within climate dynamics the presence of dissipative phenomena is expected to dump such integration. Then, dissipation introduces a characteristic time scale that marks the temporal horizon for the decay of the fluctuations toward the mean value and also oceanic processes approach white noise asymptotically (e.g., Von Storch et al, 2001).
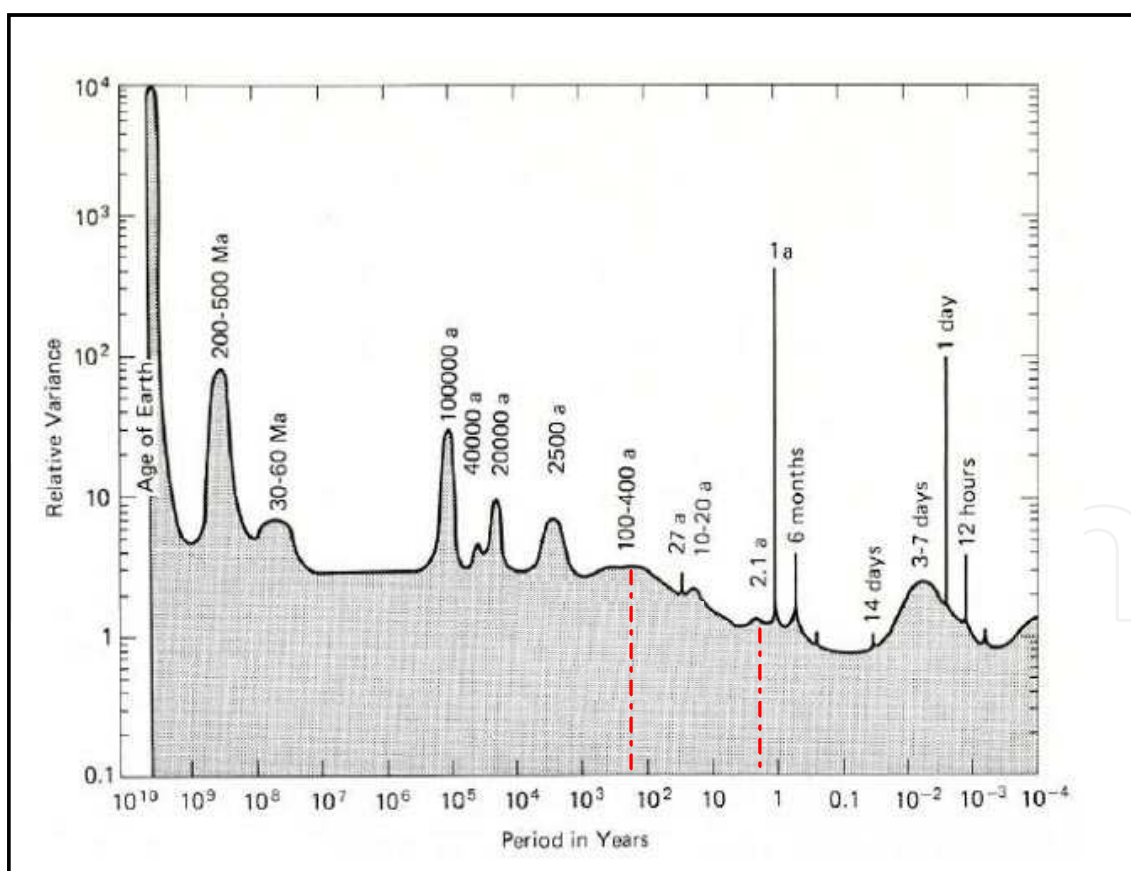

Fig. 1. Idealized sketch of the planetary climate variance spectrum (after Mitchell 1976).

To this day, the necessity of understanding the actual origin of the climate variability in the entire spectral range is still recognised as a "primary goal" of the climate research, especially

if we aim to address the impact of human activities on climate. Currently, the availability of historical records of atmospheric temperature, which is the key variable of any terrestrial process, and the possibility of enlarging the observational time window back to about 400,000 years ago (proxy paleoclimatic data) give us the unique opportunity to get realistic insights into the correlation structures that characterise climate regimes from the meteorological to the glacial-interglacial domain.

Contextually, the development of new mathematical-statistical tools, devised for enhancing specific correlation features (e.g. fractal persistence), make it possible to better discriminate such correlations from structures ascribable to more traditional superpositions of fluctuations and cycles. For many years, the scientific community has worked to rightly interpret the collection of observational data in order to improve the current understanding of the climate dynamics, evaluate the performances of models, and detect signatures of climate change blurred within regime variability. In particular, many works have focused on red spectral patterns in order to explore the possibility that the scale free dynamics typical of fractals, either non stationary (fractal Brownian motion) or stationary (fractional Brownian noise) (Mandelbrot & van Ness, 1968), could provide a description of climate better than the traditional one. A wide literature, based on both classical and new mathematical-statistical tools, is now available which reports analysis results and possible dynamical scenarios able to explain the sample time scale laws (e.g.,Konscielny-Bunde et al., 1996, 1998; Govindan et al., 2001;Eichner et al., 2003; Kurnaz, 2004; Varotsos et al., 2006; Vecchio & Carbone, 2010). These works suggest long range persistence (power law correlation) rather than scale dependence (exponential correlation) as a good statistical paradigm for explaining the climate spectrum redness on scales up to about 10^2 years. Also some analyses of pre-historical records (Pelletier, 1998; Huybers & Curry, 2006) support scale-invariance, since a random walk spectrum appears in the time scale range from 10^2 to 10^4 years. In both historical and pre-historical climate, scale separation seems to fail giving place to a continuum of self-organized scales. In this case, weather would be the only dynamical framework where it works well.

In spite of the wide consensus around these studies, there are contradictory results about the universality of the scaling and the dependence of the exponent on the distance to sea (e.g., Vyushin et al., 2004a, 2004b; Blender and Fraedrich, 2004). More in general the interpretation of such a scaling is rather controversial because of the many drawbacks of the methodologies adopted (e.g., Hu, 2001; Kantelhardt, 2001; Metzler, 2003; Mauran et al., 2004; Gao et al., 2006; Rust, 2006; Lanfredi et al, 2009, Simoniello et al, 2009).

This chapter discusses the state of the art of the studies of historical time series of atmospheric temperature, particularly focused on the interpretation of redness, and provides new analysis results for enhancing the debate on paleoclimatic observations. The core of the chapter is the discussion of the correlation structures estimated from observational data and their reliability. This is a typical problem of statistical inference that is crucial for identifying the right class of dynamical models to be used in the climate modelling. It is shown that the most popular recent interpretations, supporting power-law correlation, are not the only possible. The traditional simpler explanations are also acceptable and may work better than the complex ones. The discussion is inserted into the framework of the stochastic approach to the climate approximation, although our arguments are useful for climate modelling also within a non-stochastic approach to the problem.

The chapter is organised according to the following principal points:

Section 2 summarises the main physical and statistical concepts and tools used in the chapter. A short overview of the basic models and operational implications concerning scale separation and scale invariance is provided; analysis tools and their potential weak points are discussed. Section 3 discusses the analyses of historical and pre-historical data. Detailed statistical estimates and literature results are provided in order to support the discussion. Then, the debate on the dynamical nature of redness is extended to millennial time scales. Finally, section 4 concerns the conclusive part of the chapter.

2. Basic concepts and statistical tools

In this Section we summarise the main physical and statistical concepts and tools used in the chapter. These substantially concern the main general forms of correlation, scale dependence (short-range correlation) and scale invariance (long-range correlation), which are useful for the selection of the right class of stochastic models for climate. Of course, the discussion is not exhaustive but merely aims to provide the basic background that is necessary for the understanding of the chapter's content.

2.1 Autoregressive processes, scale dependence, and their role in the traditional stochastic climate

Stationary stochastic processes are often fruitfully modelled by means of autoregressive processes, which are filters whose input is a Gaussian independent process (white noise) ε_t (e.g., Jenkins & Watts, 1968). The output of an autoregressive process AR(p) of order p is:

$$X_t = \sum_{i=1}^{p} a_i X_{t-i} + \varepsilon_t \tag{1}$$

where (a_i) are the autoregressive coefficients and ε_t is a Gaussian random process with zero mean and variance σ^2. In particular, the paradigmatic model of the meteorological fluctuations is the first order autoregressive process AR(1):

$$X_t = a X_{t-i} + \varepsilon_t ; \qquad |a| < 1 \tag{2}$$

where the index t indicates the daily step. The autocovariance function is:

$$< X_t X_{t+n} > = \frac{|a|^n}{1-a^2} \sigma^2 \tag{3}$$

This last decays with the characteristic length $\tau = -1/ln(a)$. For continuous processes, the correlation function is:

$$\rho(\tau) = e^{-t/\tau} \tag{4}$$

For very long time scales AR(1) is completely stationary with variance:

$$< X_t^2 > = \frac{1}{1-a^2} \sigma^2 \qquad\qquad t \gg \tau \tag{5}$$

AR(1) is the most simple example of scale-dependent process: for t<<τ it is strongly correlated whereas it becomes a white noise for t>>τ. Within the traditional approach to climate approximation, this white noise describes the variability of meteorological variables in a scale range satisfying the condition:

$$\tau_m << \Delta t << \tau_c \tag{6}$$

where τ_m is the meteorological characteristic scale (a few days) and τ_c is the closest characteristic scale of climate (e.g. that of the oceans). More in general, it describes elementary stochastic processes whose superposition can generate redness through the progressive addition of variance. In fact, according to Eqs. 3 and 5, the fluctuations of an AR(1) produce low variance (high covariance) on scales shortest than its characteristic one; such a variance increases with scale up to the value in Eq. 5 on asymptotic scales. Roughly speaking, if we consider the superposition of different first order autoregressive processes AR_i (1) (*i=1,…,n*) and separated time scales $\tau_1 << … << \tau_n$, the total process behaves as AR_1 (1) for $t << \tau_2$ and its variance increases of a step $\sigma_i^2 / (1 - a_i^2)$ any time we exceed the scale τ_i thus producing a red accumulation.

2.2 Fractional Brownian motion, fractional Gaussian Noise and the concept of scale invariance

Fractional Brownian motion and fractional Gaussian noise, which were defined in (Mandelbrot & Van Ness, 1968), generalize Brownian motion and white noise, respectively.
The time trace *B(t)* of a Brownian motion (random walk) is characterized by independent increments *B(t+τ)-B(t)* having a Gaussian distribution. Such increments have mean zero and variance $|\tau|$; the mean separation between two points is proportional to the square root of the time separation:

$$| B(t+\tau) - B(t) | \propto | \tau |^{1/2} \tag{7}$$

Mandelbrot & Van Ness (1968) introduced the family of fractional Brownian motions (fBm's) by generalizing the Eq. 7.
FBm's are random variables with Gaussian increments satisfying the condition:

$$| B^H(t+\tau) - B^H(t) | \propto | \tau |^H \qquad (0<H<1) \tag{8}$$

where the exponent *H* is the Hurst's coefficient. Thus, ordinary random walk coincides with an *fBm* with *H=0.5*. For discrete times it can be approximated by summing up a white noise $w = \{ w_k : k = 0,1,.... \}$:

$$B_n = \sum_0^n w_k \qquad (n=0,1,…) \tag{9}$$

Equivalently, we can define the incremental process $z^H = \{ z_k^H : k = 0,1,.... \}$ of an *fBm* such that:

$$B_n^H = \sum_0^n z_k^H \qquad (n=0,1,…) \tag{10}$$

thus obtaining a fractal generalization of white noise which is called fractional Gaussian noise (*fGn*). FGn has a standard normal distribution for every *k*; the corresponding autocorrelation function $\rho(.)$ is:

$$\rho(\Delta k) = \tfrac{1}{2}\left[\left|\Delta k - 1\right|^{2H} - 2\Delta k^{2H} + \left|\Delta k + 1\right|^{2H}\right] \tag{11}$$

If *H = 0.5*, $\rho(\Delta k) = 0$ for $\Delta k \neq 0$. This condition brings back to ordinary Brownian motion, which has independent increments. In all the other cases *fGn* is a stationary process whose covariance is non zero for any finite Δk.

The Hurst coefficient *H* provides a measure of the persistence properties of the process according to the following scheme:

-   *0<H<0.5* $\rho(\Delta k) < 0$ *:* all points of an *fGn* separated by a lag time Δk are negatively correlated ; both *fGn* and the corresponding integral *fBm* are **anti-persistent**.

-   *H=0.5* $\rho(\Delta k) = 0$ *:* *fGn* is **independent** and the corresponding motion is the classical random walk.

-   *0.5<H<1* $\rho(\Delta k) > 0$ *:* all points of *fGn* separated by a lag time Δk are positively correlated; both *fGn* and the corresponding *fBm* are **persistent**.

The correlation of *fGn* expresses scale free interdependence and decays as a power law. For continuous times $\rho(\tau) \propto \tau^{-\gamma}$ (*γ=2-2H*). The case *γ>0.5* characterizing persistent processes is particularly interesting since the theoretical correlation implies non zero probability that disturbances survive on times as long as infinity (long range memory).

Such ideal processes may be useful within empirical studies aiming to describe observational stationary time series which show interdependence between very distant samples without approaching white noise. In these cases, the most classical models that are characterized by exponential decorrelation $\rho(\tau) = e^{-\frac{t}{\tau}}$ (e.g., autoregressive processes) could fail to account for such a long-range dependence.

2.3 Drawbacks of time series analysis for the detection of scale invariance; detrended fluctuation analysis

Generally, the investigation of time series aims to identify a class of theoretical processes able to synthesize some given correlation features of observational data: the class of the processes is assumed to be unknown. As a consequence, in order to propose a given model as a realistic descriptor of the investigated dynamics, we have to demonstrate both the compatibility of the tested theoretical correlation structure with that estimated from data (necessary condition) and to exclude any other alternative forms of correlation (sufficient condition).

Actually, the procedures that are used to identify the existence of power-law correlation do not allow us to satisfy both these conditions. It is well known that the variance spectrum is very sensitive to any form of non stationary behaviour. It is suitable for investigating stationary or cyclo-stationary signals or, more in general, signals with weak local features. As far as climatic time series, this condition cannot be guaranteed. Any external forcing such as volcanic eruptions and externally induced temporary warming/cooling trends can produce misleading results.

In order to avoid these drawbacks, some authors developed alternative tools, such as Detrended Fluctuation Analysis (DFA) (Peng et al, 1995), aiming to minimize externally-induced non-stationary effects describable in the form of low-order polynomials. 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:

$$F(n) = \sqrt{\sum_{k=1}^{N} \left[y(k) - y_n(k) \right]^2 / N}$$ (12)

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 ($\alpha=H$ for fGn). In this chapter the 2nd-order Detrending (DFA2) is adopted in order to minimize the effects of discontinuities and linear trends.

This methodology, that is generally considered the most powerful for identifying fGn, may produce many false positive results. This point is well stressed in Mauran et al., (2004). This is a method developed to discover fractals blurred in noise. In practice, it intrinsically postulates that a fractal is present and try to estimate the scaling coefficient minimizing external disturbances. It satisfies the necessary condition above (if a fractal is present it is generally able to find it) but is not able to satisfy the sufficient condition, since if there is not any fractal the estimation of a linear best fit in a log-log plot of sample statistics is not sufficient for supporting the actual existence of a power law. In particular, log-log collinearity should be carefully verified.

3. Results from time series analysis of atmospheric temperature

In this Section we discuss some examples of analyses of temperature time series aiming to detect long range persistence. We refer to bibliography for in-depth information.

3.1 Historical data

The rationale behind most of the investigations on historical data is the more or less explicit use of white noise as null hypothesis.

Within the classical stochastic approach to climate approximation the fastest processes we deal with are the meteorological processes, whose time scale is considered well-separated from all the slower climatic time scales. Such a meteorological variability has been traditionally explained by low-order autoregressive processes such as the paradigmatic first-order autoregressive process (AR1):

$$X_t = a X_{t-i} + \varepsilon_t ;$$ (13)

where X_i is the meteorological variable, a is the first-order autocorrelation coefficient, and ε_i represents white noise. According to this model, the parameter a accounts for rapid inter-day 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., 2000; Matsoukas et al., 2000; Haggerty et al., 2002; Bunde et al., 2002; Kandelhardt et al., 2003, 2006; Blender and Fraedrich, 2003), many researches have focused on historical atmospheric temperature time series for exploring the possibility that long range persistence characterizes climate after the meteorological correlation is decayed (e.g., Konscielny-Bunde et al., 1996, 1998; Govindan et al., 2001; Eichner et al., 2003; Kurnaz, 2004; Varotsos et al., 2006).

Their analyses, based on the estimation of the Hurst coefficient prevalently by means of DFA, seem to put into evidence slightly long range persistent features and their conclusion is that the asymptotic noise ε_i is not white but is a power law correlated noise (see Kiraly & Janosi, 2002 for a fractal version of Eq. 13).

According to these works Fractional Gaussian noise 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.
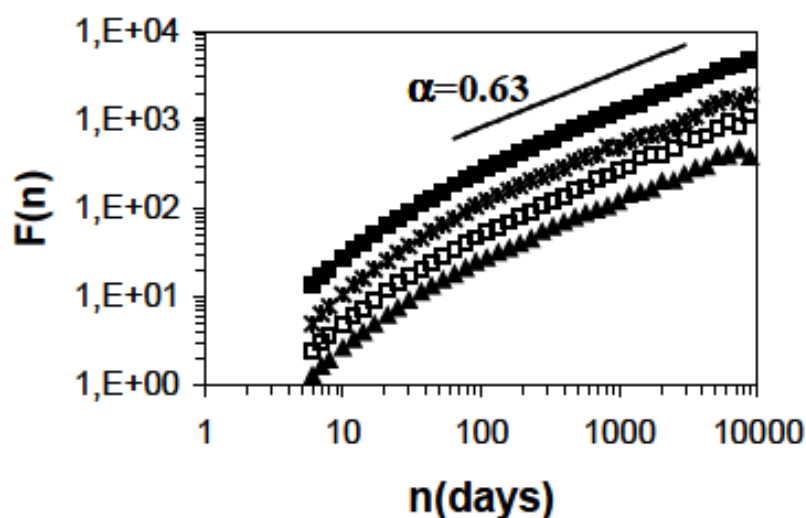
Fig. 2. Plot of the detrended fluctuation function for daily atmospheric temperature time series (Klein Tang, 2002) recorded in Prague (filled squares), Wien (stars), St. Petersburg (empty squares), Potsdam (triangles) (after Lanfredi et al, 2009).

Fig. 2 shows the results of DFA applied to four atmospheric temperature time series widely analysed literature (Lanfredi et al, 2009 and references therein).

The apparent linear behaviour of the fluctuation function on decadal scales is rather evident and the value of the Hurst coefficient greater than 0.5 indicates a long range persistent behaviour. Nevertheless, just the well known redness of the climatic spectrum suggests that white noise is not the right null hypothesis against long range persistence. The actual problem is to establish whether the power law is the best representation for the atmospheric temperature correlation or instead alternative time scale laws are acceptable. In practice there is a problem of functional form goodness for the linear fit. Fig.3 (Lanfredi et al., 2009) shows the residuals from the power law best fit of Fig. 2 which should be a stationary noise in the time range where the time series is fractal. On the contrary, the residuals are arranged in a non-linear way in all the cases.
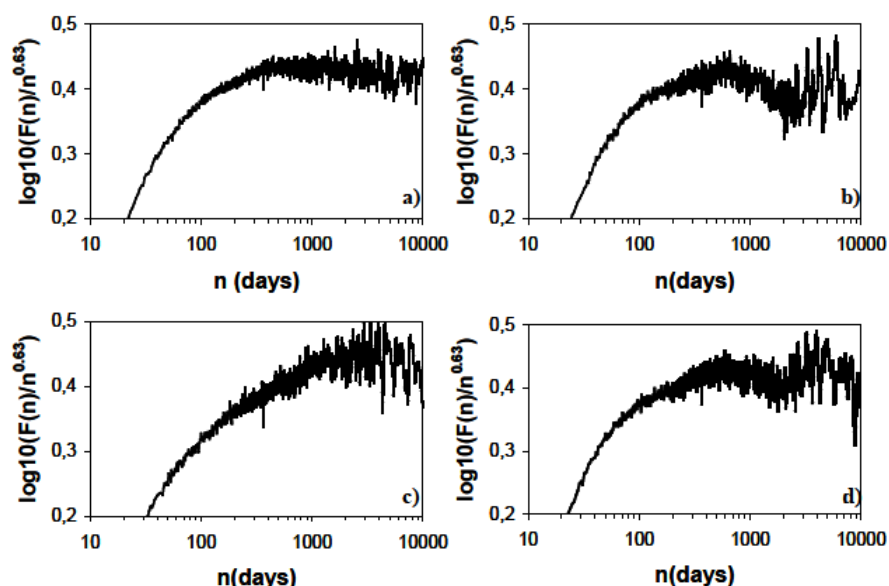
Fig. 3. Plots of the ratio $F(n)/n^{\alpha}$ in logarithmic scale for the four time series of Fig. 2: (a) Prague; (b)Wien; (c) St. Petersburg; (d) Potsdam (after Lanfredi et al., 2009).
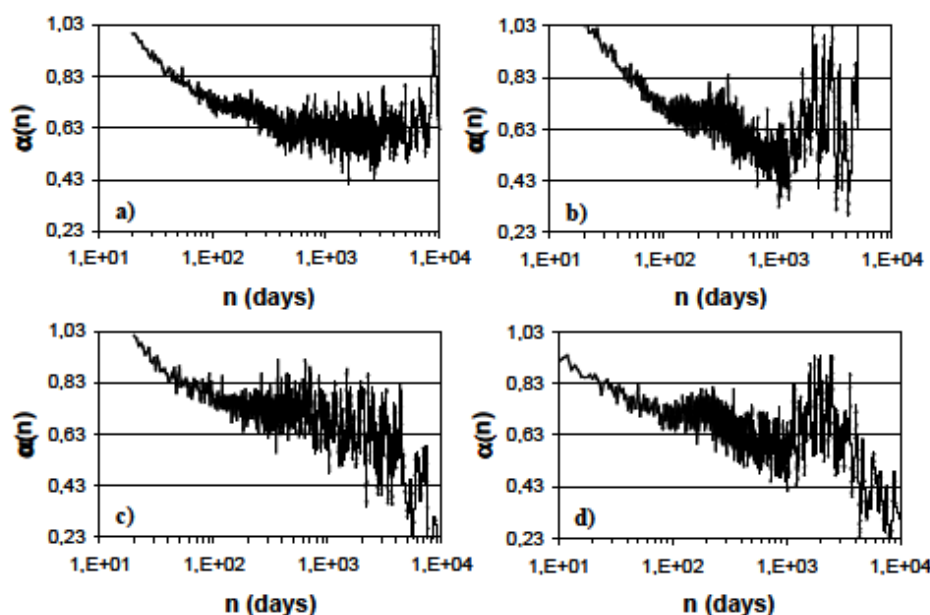

Fig. 4. Estimates of $\alpha(n)$ for (a) Prague; (b)Wien; (c) St. Petersburg; (d) Potsdam (after Lanfredi et al., 2009).

In addition, within the scaling regime, the scale invariant law $F(kn)=kF(n)$ should hold for any k. Thus, the function $\alpha(n)=log_k[F(kn)/F(n)]$ should provide an estimation of the local scaling coefficient. Again, $\alpha(n)$ should be a stationary noise where a scaling regimes occurs. Fig. 4 shows the estimates of $\alpha(n)$ for the four time series of Fig. 2. On short time scales the high value of $\alpha(n)$ accounts for a strong correlation that progressively decays approaching a noised and irregular behaviour that does not allow us to detect scaling regimes unquestionably. Most likely, the apparent scaling is due to the emergence of slower fluctuations that add "shelves" (Mitchell,1976) to the time series variance.

In order to assess how short range dependent processes appear when examined by means of fractal tools, we can investigate time series simulated on the basis of observational data and modelled according to scale separation (Lanfredi et al, 2009).

Fig. 5 and 6 show the analysis results of a simple two-scales (weather-climate) process, modelled on the basis of the autocorrelation function of the Prague's data. The analogies with the real data (Figs 2,3 and 4) are very impressive. The two-scale model is able to account for the whole results obtained from the fractal investigation. The mechanism that produces scaling is clear. Correctly, the total fluctuation function $F(n)$ ends as a white noise (Fig. 5b) only in the latest part of the plot. Nevertheless, since the variance produced by the slow climatic variable emerges only on the long time scales, if we try to fit the function globally from the short to the long time scales (Fig. 5a), a spurious scaling occurs for the presence of the variance shelf.
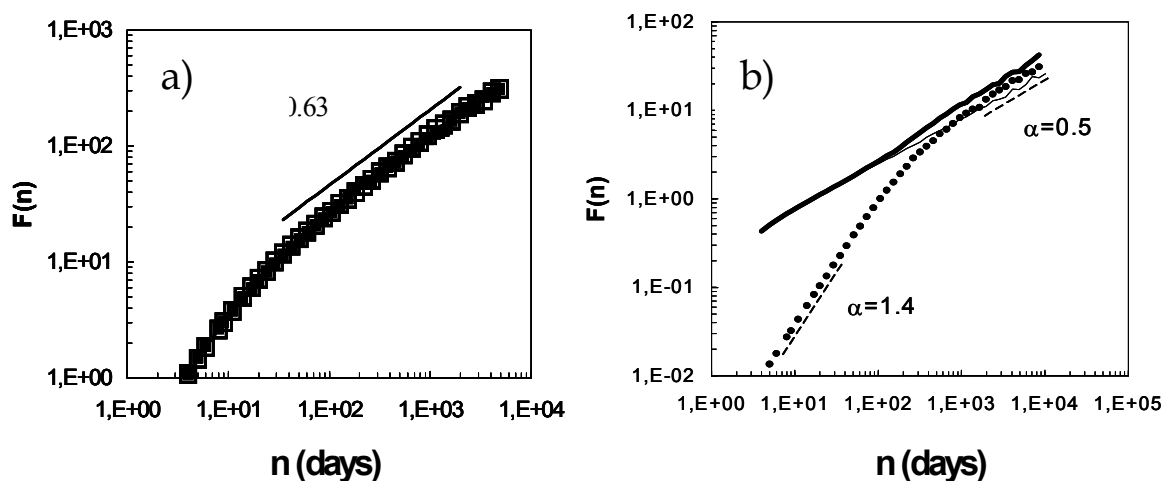
Fig. 5. a) Results of DFA for real (filled squares) and simulated (empty squares) anomalies. The continuous line shows the empirical power law reported in literature; b) effect of an hidden long scale within an asymptotic noise, the high scaling coefficient of the hidden process $\alpha=1.4$ on short scales is an indication of strong correlation and is compatible with values estimated for the ocean (after Lanfredi et al, 2009).
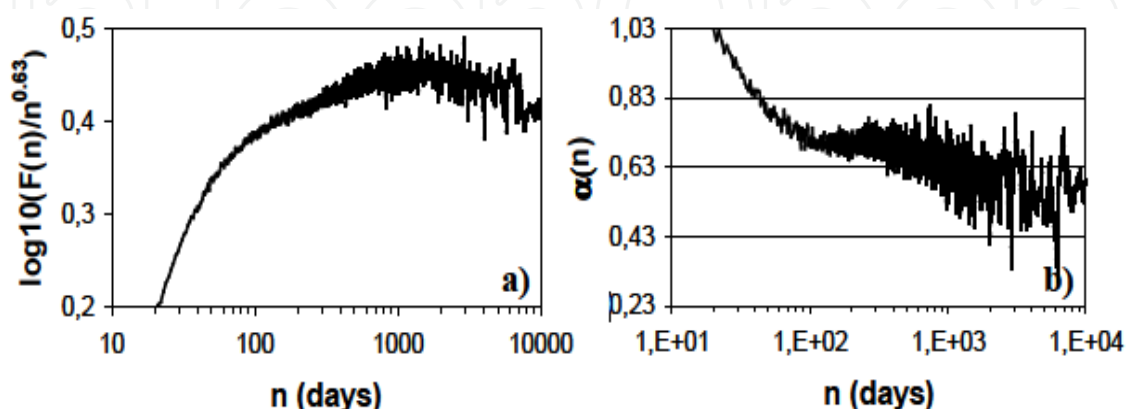

Fig. 6. Residuals from the linear best fit, and estimation of the local scaling exponent of a two-scales (weather-climate) autoregressive process (after Lanfredi et al, 2009).

3.2 Paleoclimatic data

The temperature time series obtained from the Vostok ice core dataset (Petit et al, 1999) provides a unique source of information about climate changes over glaciological scales.

Although unevenly sampled in time and affected by reconstruction errors, such as non-temperature effects, observational uncertainty, age-model uncertainty, etc., it includes structures generated by those time scale laws we are searching for. Above all, they can inform us about possible common correlation structures unifying climate dynamics on historical and paloclimatic eras.

Fig. 7 shows this paleorecord that describes temperature variability for the past 420,000 years. The time series appears to be rather noised even if some near systematic behaviours are detectable. Among them, the longest oscillations (Milankovitch cycles) account for the alternation between glacial and interglacial eras. Although the astronomical variability that drives them are known to be a combination of cyclical changes of the Earth-Sun geometry (eccentricity, obliquity, precession), there is not yet a shared interpretation of the underlying dynamics (e.g., Meyers et al 2008). These data include information on the effects of the so-called "Pacemaker of the Ice Ages " (Hayes, et al., 1976) on the terrestrial internal climatic variability. Just this variability under the action of the astronomical forcing could provide useful insights on the mechanisms that govern the mutual interactions between the different climatic subsystems. Also in this case, we do not discuss this specific dynamical problem but illustrate the difficulty related to the inference of time scale laws from this dataset.
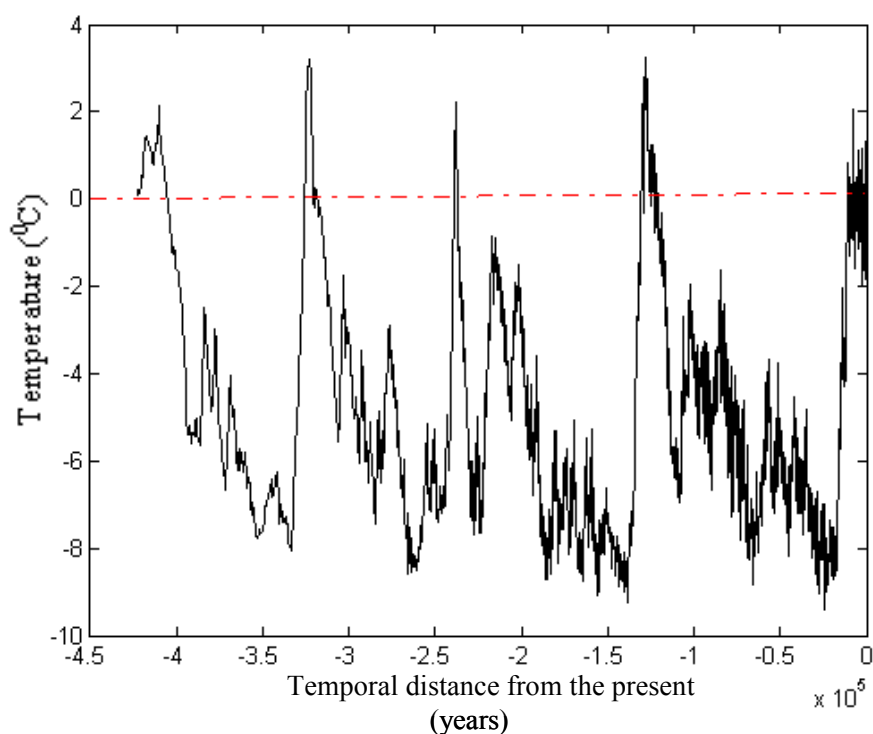

Fig. 7. Reconstructed temperature data from the Vostok Ice Core dataset (Petit et al., 1999). Temperature is the difference from the mean recent time value (red line).

Maybe, the most famous work proposing scale invariance as the main tool for explaining climate variability over millennia is that by Huybers & Curry, (2006). It gathers both historical and paleoclimatic data and discusses their power spectrum within an unified theory based on a fractal continuum of time scales. The estimated variance spectrum is reported in Fig. 8.

The low frequency scaling coefficient for the paleorecord corresponds to a value of the Hurst's coefficient H=0.32, which is signature of anti-persistent fractional Brownian motion. Quite similar results were also found by Pelletier, (1998) who estimated a coefficient compatible with random walk.
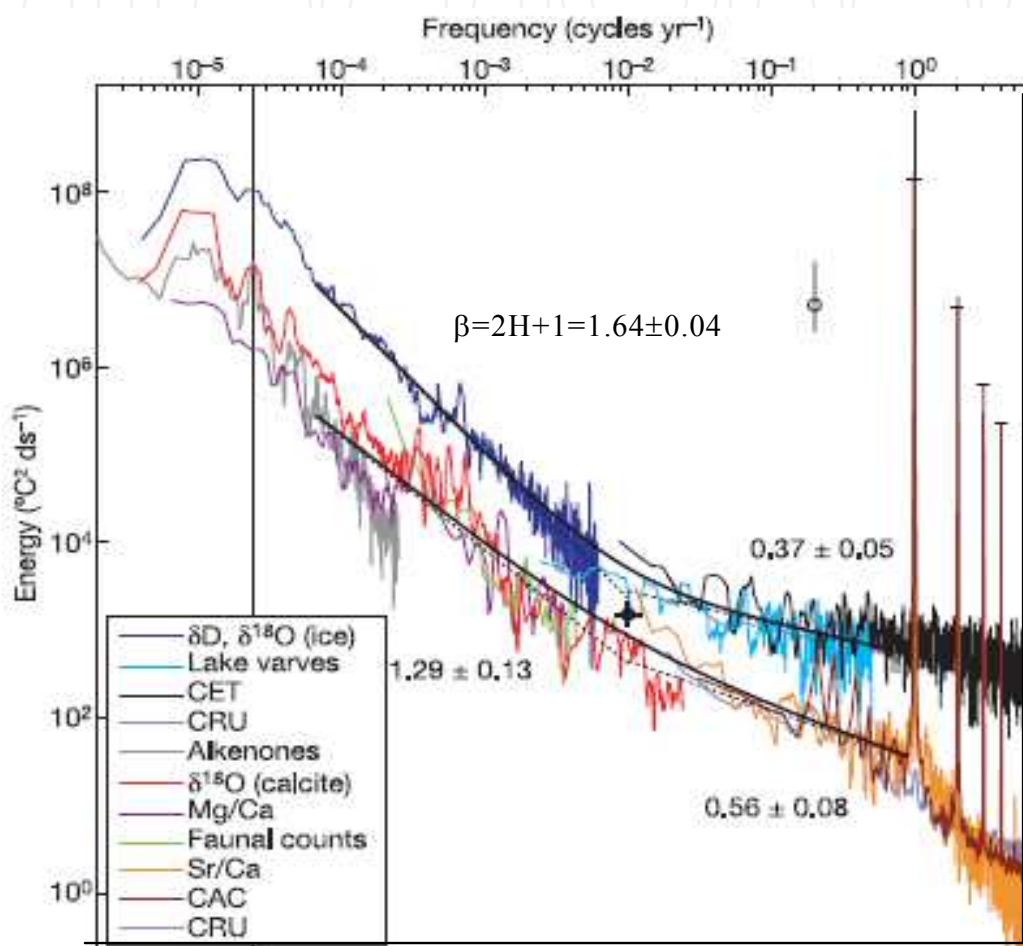
Fig. 8. Sample estimation of the planetary climate spectrum (after Huybers & Curry,2006). The parameter β is the estimated scaling coefficient.

The visual inspection of this spectrum in the low frequency range , so as it is, raises some questions. Differently from the high frequency cycles (annual frequency and sub-harmonics), which appear as spikes well separated from the continuous spectrum of the stochastic component, the millennial cycles are difficult to be separated from noise: it is necessary to know them a priori for interpreting the spectrum correctly. As already specified above, the variance spectrum is not the best tool for investigating complex signals where trends and oscillations could introduce spurious scaling (Gao et al, 2006). Huybers & Curry (2006) estimated the paleorecord scaling in the frequency range between 1/100 and 1/15,000 years to minimize the influence from the Milankovitch bands. Nevertheless, cyclic trends occur in the analysed band too (e. g., Kerr, 1996).

In order to delve into this problem we can investigate time scale laws in the time domain by estimating the second order structure function (Kolmogorov, 1941):

$$\gamma(\tau) = < [X(t + \tau) - X(t)]^2 > \qquad (14)$$

which is the best statistical tool for studying fractional Brownian motion, since it can be applied to non-stationary data and $\gamma(\tau) \propto \tau^{2H}$ when the time series $X(t)$ is an *fBm*. Second order structure function coincides with the variogram used in Geostatistics (Cressie,1993), which is a well known tool for investigating time scale dependence also when data are unevenly sampled.
Fig. 9 illustrates the structure function of the Vostok time series normalised to $2\sigma^2_X$.
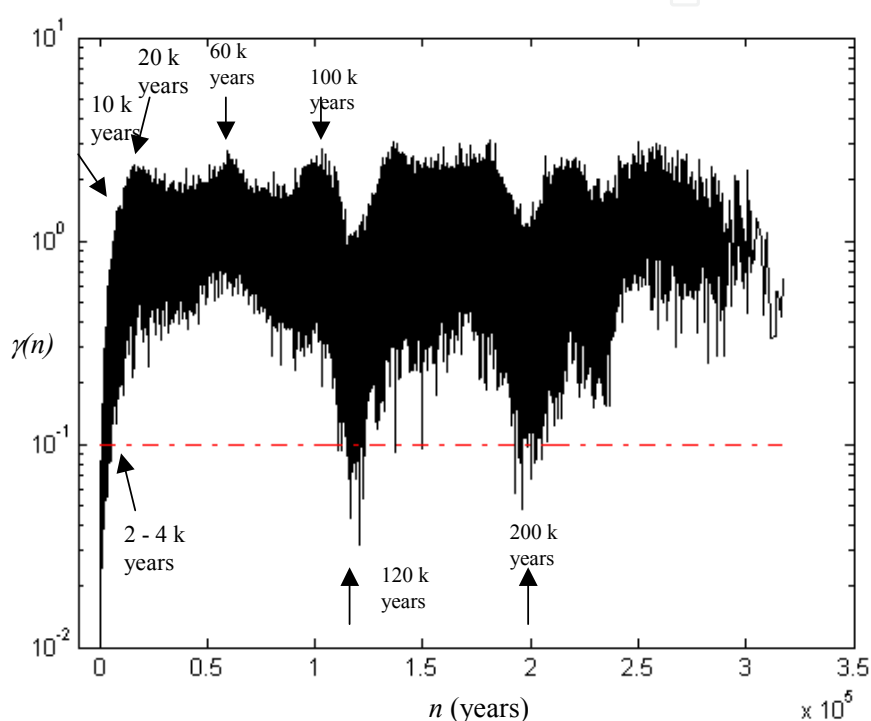
Fig. 9. Second order structure function of the Vostok Ice Core dataset. Arrows indicates approximately the time scales where cycles exhibit minimum or maximum values. The level $\gamma(\tau) = 1$ corresponds to the variance of the total time series.

Differently from the sample spectrum, the structure function reveals long time oscillations explicitly. They are clear in spite of the strong noised character of the estimations due to the uneven and limited sampling etc.. In the time domain, maximum values are associated to odd multiple of semiperiods whereas minimum values correspond to multiple periods. In a composition of cycles and noises, the minimum values reached in the periodic part of $\gamma(n)$ (red dashed line in Fig. 8) mark the percentage contribution due to pure noise. The scale where this plateau is intercepted for the first time (a few thousand of years) marks the crossover between the scales where the truly stochastic noise is observable and that where the contribution of the cycles starts to appear. Then the scaling would occur in a scale range where the non stationary character of the oscillations contaminates the variance of the noise. By looking at Fig. 10 in the temporal range where scaling should appear (red line from 10^2 to 1.5×10^4 years), a direct estimation provides the value H=0.53, which is in a rather good

agreement with the estimations of Pelletier (1998). Nevertheless, we can observe that the scales shorter than 10^3 years are evidently not collinear with the subsequent ones. The same is true above 10^4 years, where $\gamma(n)$ appears flatter. If we estimate H by progressively shortening the Huybers & Curry range from the short scale side, its value increases. The same is true if we shorten it by starting from the long time scales. The maximum value $H=0.6$ is obtained about in the middle of the initial range but this does cover not even one decade, which is the minimum requirement for keeping confidence in scale invariance. In addition, we can note that the apparent linearity ends with a maximum value that corresponds to one half period of the ~20 k years oscillation. The central about linear behaviour seems to be an inflection transient between the short time scales (concavity up) and those belonging to cycles where the function $\gamma(n)$ exhibits a different curvature (concavity down).
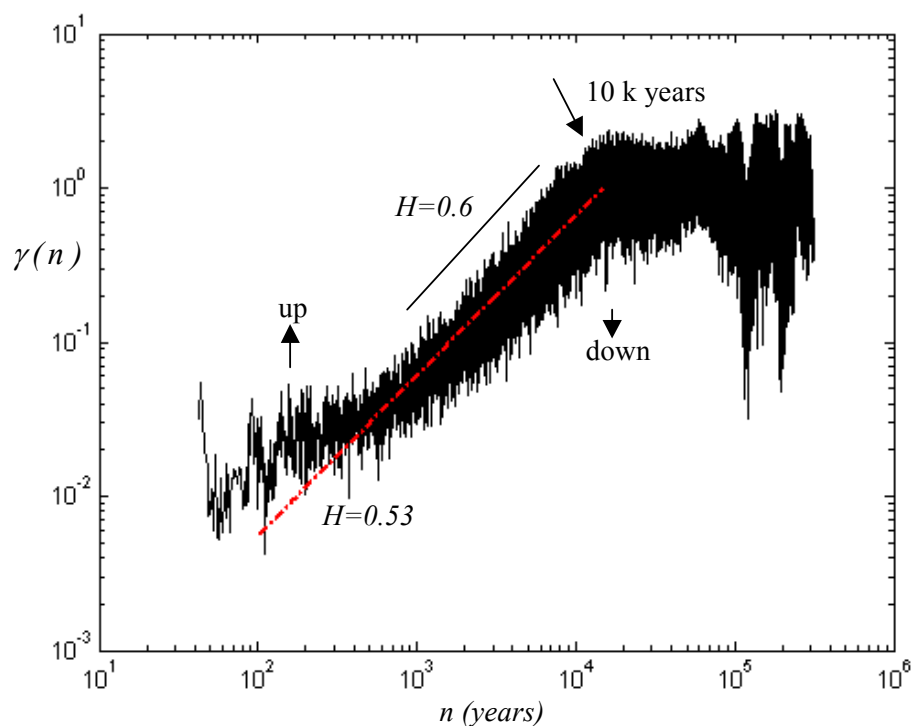
Fig. 10. As Fig. 9 but in double logarithmic scale. The peak at about 10 k years is the maximum anticorrelation associated to a cycle of about 20 k years. The red line is the best fit computed on the time scales indicated by Huybers & Curry (2006): 10^2 years- 1.5×10^3 years. Arrows indicate the concavity semi-planes.

4. Conclusion

In all the studies on the dynamics of the natural world, observational time series play a fundamental role since they are the main source of information for inferring the underlying causal mechanisms. Especially in a stochastic context, when the number of degree of freedom is high, observational time series can provide those time scale laws that rule temporal correlation thus helping us to identify the right reference class of theoretical models. Nevertheless, the interpretation of time laws estimated from real data can be rather difficult because the analysis results can be rather ambiguous in many cases. Dynamical

inferences from climate observations fall just in this class. The analysis results illustrated in this chapter put into evidence that no conclusive interpretation of the sample variance spectrum is available yet. It is clear that the analyses performed have to be carefully supervised, preferring those mathematical and statistical tools that are less sensitive to local (in time) disturbances, trends, and cycles that can trick analysts. Spurious scaling can easily appear thus suggesting an erroneous modelling of the deep dynamical characteristics of the climate. Future work should address the problem of temporal persistence not only by demonstrating that climate redness is compatible with scale invariance (necessary condition) but also by demonstrating that it "is not" compatible with a progressive coming out of a few ever slower scale-dependent processes (sufficient condition).

5. Acknowledgment

6. References

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Climate Change - Geophysical Foundations and Ecological Effects

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