How Predictable are Temperature-series Undergoing Noise-controlled Dynamics in the Mediterranean *

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Introduction

Su i dodici del ciel segni divisi
Regola il mondo, e le stagioni alterna.
Partesi il globo in cinque zone, e l'una
Di loro ai raggi del cocente sole …
Dei poli estremi, da perpetuo gelo …
Ma fra queste, e la prima in mezzo chiuse
Stan le altre due, che temperate e miti
Concesse il Ciel ai miseri mortali.

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Scientists have long employed Global Circulation Models (GCMs) to answer about the future of the Earth's climate because they provide the opportunity to vary the parameters involved. However, the GCMs establish a limited number of functional relationships and forcing agents and are known to be affected by a large degree of uncertainty (modelling, downscaling, initialization). Besides an incomplete knowledge or understanding of a particular process (epistemic uncertainty), a central problem are the unpredictability, partly inconsistent with the observed warming during the industrial period (Knutti et al., 2008). Another restraint of the GCMs is that it is unlike that this mixture of funtional relationships and alternative parameterization may be used by a large community of users and for decision-making, being limited to special interest and minority groups of scientists needing the low-flexibility this makes available.

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Attempts are being made by the scientic community towards alternative solutions to the overrepresented GCMs. Concerning the predictability efforts, approaches suitable for climate studies (other than the GCMs) are referred by Alexiadis (2007) and Viola et al. (2010): Model-Based Methods (MBMs), Planet's Dynamic Models (PDMs), and models built upon Time Series Analysis (TSA). They represent the climate system in a conceptual way. This is why they can be useful for a broad range of users to gain qualitative understanding of both the climate system and the relationship between the models and the modelled real-world system. The atmosphere itself remains, however, the most important limiting factor to human ability to forecast climate, and the unpredictability inherent to the system is more important than computer power or data availability and accuracy (Singleton, 2010). It is growing in the scientific community awareness that the atmosphere and oceans form a complex interactive system with unpredictable shift and unexpected extremes (e.g., Mazzarella, 2009). Therefore, we should expect a degree of irreducible inaccuracy in quantitative correspondences with nature, even with plausibly formulated models and careful calibration (tuning) against several empirical measures (McWilliams, 2007).

In the meanwhile that new Earth climate models (e.g., those of intermediate complexity, Weber, 2010) become more realistic for decadal prediction, approaches based on time-series analysis which tries to build a model from experimental data can be addressed for exploratory and forecasting purposes. This would make climate research more reproducible by a large community of scientists and managers that can re-create the research outcomes. In such respect, online statistical tools can accommodate climate historical records by means of memory-based autoregressive methods. A similar approach, reversing the direction of the natural progression of time, allows to "experience" in reality what happened in the past in order to search out a "attractor memory" (after Nicolis and Nicolis, 1986). The response of these model is important because it takes into account all the possible natural processes involved in the evolution of climate records (Enzi and Camuffo, 1991). In this context, a possible approach consists to see the Earth climatic system as qualifyied by a linear-and-chaotic attractor. Therefore, by decomposing a climatic time-series as a sum of explicit periodic-regimes and a random noise component, these components can be modelled separately (after Nikovski and Ramachandran, 2009). However, the classical time-series prediction methodologies that are based on auto-regressive exponential models can present large noise making very difficult their predictability.

This contribution deals with time series analysis related to temperature dynamics. It explores a long temperature series, transformed by means of Empirical Mode Decomposition (EMD, after Huang et al., 1998). The Mediterran Sub-regional Area (MSA) is the focus of this study because it is now available an accurate long-time series of mean winter temperatures (Diodato et al., 2010).

For the Mediterranean region, the projections by the global and regional model simulations are generally consistent with each other at the broad scale (Giorgi and Lionello, 2008). A lengthy temperature series available at fianre spatial resolution offers a unique opportunity to explore past interdecadal climate variability, and to (try to) use its internal dependence structure to replicate future temperature ramification at sub-regional scale. The sub-regional scale (as that represented by the MSA) is also important to extract information representative of natural climate variability (after Stott et al., 2010) for used in statistically based-models.

2. Data and methods

The Mediterran Sub-regional Area (MSA) it is a circum-Thyrrenian region (Figure 1), part of the larger Mediterranen Central Area (MCA) defined by Diodato and Bellocchi (2010). The MSA climate is characterized by the polar-ward (summer) and equator-ward (winter) shift of the Azores subtropical high-pressure cell (Camuffo et al., 2010).

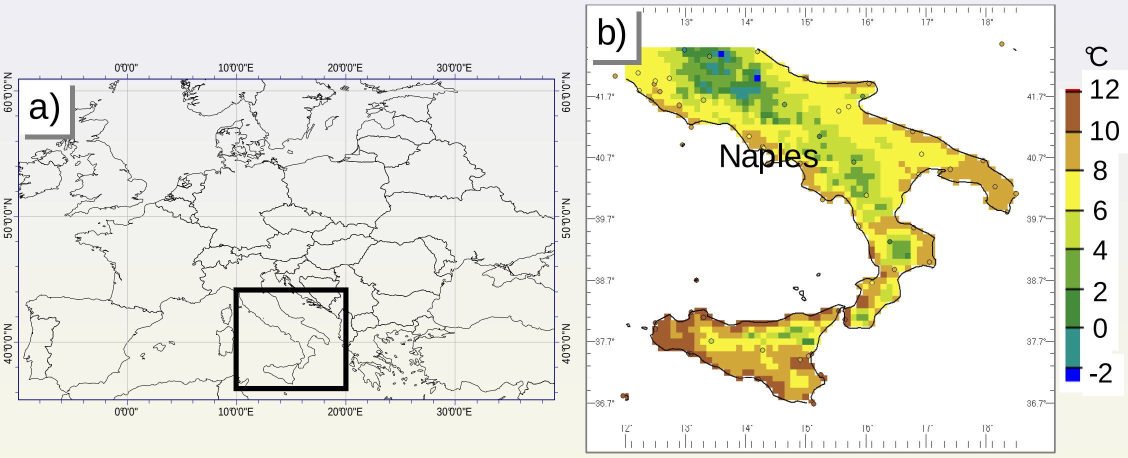

Figure 1. a): Geographical setting of Mediterranean Sub-regional Area (MSA), and b): Winter temperature pattern averaged over 1961-1990 over MSA (arranged by LocClim FAO software with 10-km resolution, http://www.fao.org/sd/locclim/srv/locclim.home).

Especially in the cold season (October-March), the area is frequently crossed by depressions generating over the Mediterranean Sea (Wigley, 1992) that, reinforced by continental north-easterly airflows, produce important fluctuations in temperature and precipitation (Barriendos Vallve and Martin-Vide, 1998). However, the MSA can be considered homogeneous with respect to temperature, as the spatial correlation map shows in Figure 1a.

The earliest regular instrumental observations started in Italy over the 17th century, when temperature readings were recorded up to eight times a day (Camuffo and Jones, 2002). However, it was only after 1860, which marked the unification of Italy, that temperatures were recorded from a dense network of stations.

In Europe, a first effort for reconstructing a long history of homogeneous dataset was made by Luterbacher et al. (2004), who produced data upscaled to a 0.25 x 0.25 degree grid resolution from past instrumental series and multi-proxy data since 1500. For the MCA, the major effort devoted to transform early, never-before utilized observations into modern-high series through rigorous quality controls, validation, correction and homogenization was possible after the 17th century (Camuffo et al., 2010).

Diodato et al. (2010) used the basic datasets of Luterbacher et al. (2004) and Camuffo et al. (2010) to generate, for the MSA, the series of winter temperatures (1698-2010) used in this work. Sources and validation of these documentary observations date since the first instrumental measurements started in Naples as early as 1727 thanks to Domenico Cirilloa and published through the Meteorological Diaries of the Royal Society of London (Figure 2, left). The observations became systematic since 1821 and were published by the Annals of the Kingdom of Naples (Figure 2, central and right).

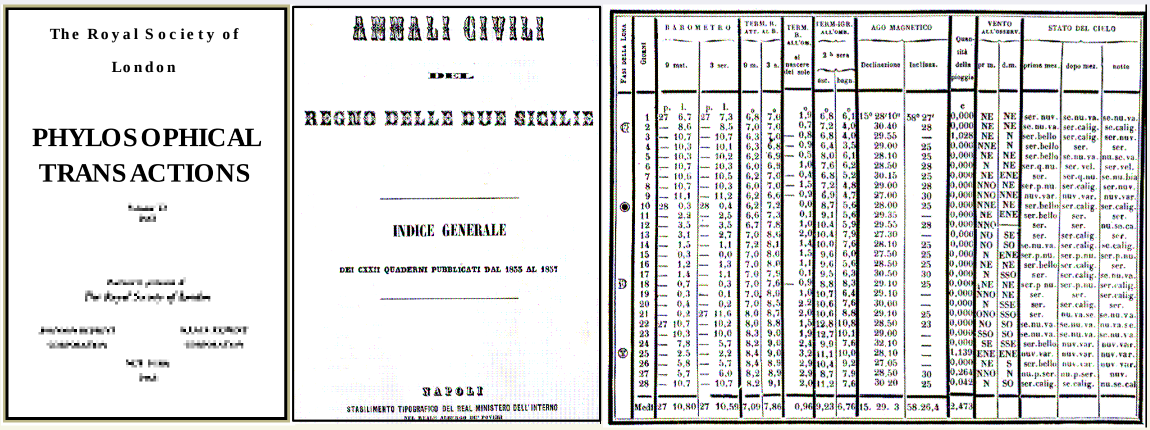

Figure 2. Cover page (left) of Philosophical Transactions (Royal Society of London), which published the first instrumental weather observations performed at Naples by Domenico Cirillo (Derham, 1733-1734). Cover page (centre) and exemplary pages (right) of the Annals of the Kingdom of Naples (edition of February 1842) which published the meteorological observations systematically performed between 1833 and 1857.

Time series are generally sequences of records of one or more observable variables of an underlying dynamical system, whose state changes with time as a function of its current state vector. The analysis of the statistically significant systematic and random fluctuations of such records provides important information for climate change studies and for statistical modelling and long-range climate forecats. The time series analysis of winter temperature series was performed by online tools: MatLab routine (http://www.mathworks.nl/matlabcentral/fileexchange/21409-empirical-mode-decomposition) for denoised temperature-series, AnClim (http://www.climahom.eu/AnClim.html, Stepanek, 2007) and Visual Recurrence Analysis (http://nonlinear.110mb.com/vra) for an exploratory data and chaotic analysis of the time-series, respectively.

2. Exploratory data analysis

Exploratory procedures aim at knowing the temporal-pattern and time-variability of the process for the original temperature-series. For winter temperature dynamics across the MSA, a non-stationarity structure was found (Figure 3a). An important finding is the existence of a compact and chaotic trajectory in time-space domain, which can be seen to evolve to certain temperature predictability (Figure 3b). This issue is explored more in-depth in the next section. Regardless of the predictability statistics, these series may be non-stationary (yet in high order moments), which makes difficult to study their evolution. With a main discontinuity period occurring around the 1960s, Figure 3a gives visual clue to the inherent complexity of Mediterranean temperature series.

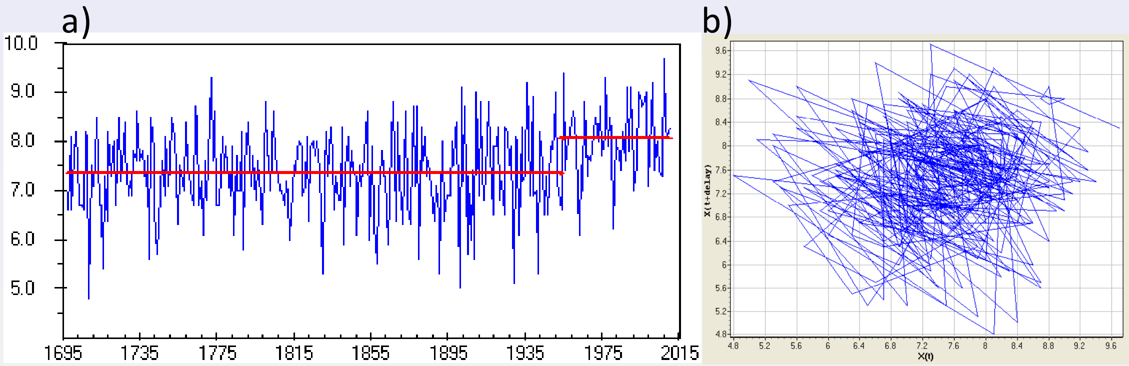

Figure 3. a): Temporal-pattern in winter temperature original-series (1698-2010) with overimposed jump in data before and after the year 1955 (horizontal lines) arranged by AnClim software, and b): Its attractor in phase-space domain, arranged by the Visual Recurrence Analysis software.

3. Time-serie pattern noise reduction and predictability

Recent advances in the field of Digital Signal Processing (DSP) have addressed the denoising of signals by using various filtering algorithms (Ingad, 2009). Moving-window techniques are commonly used for the extraction of time-varying signals from actual observations (Gather et al., 2006). However, such techniques cannot cope with the complexity of nonlinear and nonstationary phenomena. If the data are corrupted with noise at specific frequencies, Moving Average (MA) filters perform poorly by introducing biases (Ott, 1988) because they act as low-pass filters with poor ability to filter noise at individual frequency (Smith, 1999). Fast Fourier Transform (FFT) based filters provide accurate information about the frequency content of the data, which is used for filtering of noise. However, FFT assumes that the data are stationary. Noise in nonstationary data can be handled using techniques like Short-Time Fourier Transform (STFT) and wavelet transformed-based filters, developed to handle transient data corrupted with nonstationary noise (mean and variance of noise varies with respect to time). STFT is based on the principle of dividing the data into various stationary segments (mean of the signal remains constant in this segment) followed by application of an FFT-based filter for each individual segment (Cohen, 1995). STFT requires identification of an optimal window length within which the data is stationary, which is difficult. If the window size is small, it is not possible to separate narrow frequency bands. This in turn leads to difficulty in filtering narrow band noise. It is also often not possible to find large stationary segments in the data of interest. Discrete Wavelet Transform (DWT) filters are widely used to overcome the drawbacks associated with STFT filters (Mallat, 1999), but cannot be effectively used for filtering signals corrupted with narrow band and nonlinear noise sources.

More recently, Empirical Mode Decomposition (EMD), a time-domain algorithm, has been developed for handling nonstationary and nonlinear signals (Huang et al., 1998, 1999, 2006). EMD is the key part of the Hilbert–Huang Transform (HHT) method. Using the EMD, any complicated data set can be decomposed into a finite and often small number of components, which is a collection of "Intrinsic Mode Functions" (IMF). An IMF represents the characteristic features of the data at various time scales. It is an oscillatory mode as a counterpart to the simple harmonic function, but it is much more general: instead of constant amplitude and frequency in a simple harmonic component, an IMF can have variable amplitude and frequency along the time axis. In this way, the decomposition method operating in the time domain is adaptive and highly efficient. Since the decomposition is based on the local characteristic time scale of the data, it can be applied to nonlinear and nonstationary processes. Salisbury and Wimbush (2002), using Southern Oscillation Index (SOI) data, applied the HHT technique to determine whether the SOI data are sufficiently noise-free that useful predictions can be made and whether future El Niño Southern Oscillation (ENSO) events can be predicted from SOI data. Datig and Schlurmann (2004) noted that HHT is capable of differentiating between time-variant components from any given data. EMD has proven to be quite versatile in a broad range of applications for extracting signals from data generated in noisy nonlinear and nonstationary processes (Wu and Huang, 2008). Kollengodu-Subramanian et al. (2011) illustrate the effectiveness of the EMD-based filtering approach by a comparison study with MA filters, FFT- and DWT-based filtering methods. Applying the EMD algorithm to the signal *x(t)* gives:

$$x(t) = m_n(t) + \sum_{k=1}^{N} d_k(t)$$

where $m_n(t)$ is the trend component, $d_k(t)$ is the k^{th} IMF with k varying from 1 to the number of IMFs, N. Once IMFs are obtained from the EMD algorithm, the next step is to identify and eliminate the IMFs corresponding to noise components. The seminal literature discusses elaborately the EMD-based DSP filtering approach (which is not reproduced in detail here).

With the aid of the EMD procedure, a cleaner representation of winter temperature dynamics in the MSA was obtained. We have assembled temperature-series by EMD running data (Figure 4a), successively named decomposed winter temperature data [Twin(EMD)]. This is meant to reduce noise and to explore chaotic properties and predictability of original time series (after Kawamura et al., 1998). As it appears from Figure 4b, the attractor for the denoised series is in fact different from the one in Figure 3b. Although still encapsuled, we can use this new-and-manifest trajectory path as an indication of predictability.

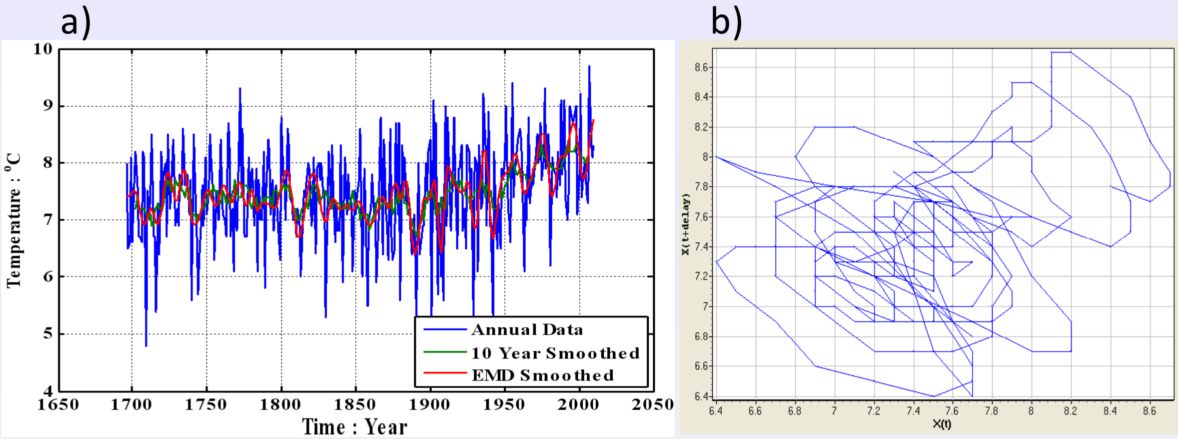

Figure 4. a) Temporal-pattern in winter temperature for the original time-series (bleu line) and for EMD- transformed data series (red curve); b): Attractor in phase-space domain for Twin(EMD) data-series.

4. Concluding remarks

In the past decades, there has been an increasing interest for the long-term climate forecasting. However, many of these studies have not adequately examined key issues, and relied on research processes that slowed the exchange of information among physical, biological and social scientists (Moss et al., 2010). Weather data are invariably corrupted with some form of noise, and noisy data are still an issue for climatology. Effective removal of noise from data is important for better understanding and interpretation of time series. In this contribution, we have applied an Empirical Mode Decomposition based approach to a winter temperature series in the Mediterranean Sub-regional Area. Time-dependent spectral representation shows signs of predicibility, and this could be the basis for creating reproducible and plausible scenarios of climate realizations (of support for the scientific community and managers alike). The authors wish to stress that all steps made in this paper do certainly need verification and further improvements. However, its significance and need for development is outlined and should encourage closer investigation by other researchers working in this field.

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References

Alexiadis A., 2007. Global warming and human activity: a model for studying the potential instability of the carbon dioxide/temperature feedback mechanism. Ecological Modelling 203, 243–256.

Barriendos Vallve M., Martin-Vide J., 1998. Secular climatic oscillations as indicated by catastrophic floods in the Spanish Mediterranean coastal area (14th–19th centuries). Climatic Change 38, 473-491.

Camuffo D., Bertolin C., Barriendos M., Dominguez-Castro F., Cocheo C., Enzi S., Sghedoni M., della Valle A., Garnier E., Alcoforado M.J., Xoplaki E., Luterbacher J., Diodato N., Maugeri M., Nunes M.F., Rodriguez R., 2010. 500-year temperature reconstruction in the Mediterranean Basin by means of documentary data and instrumental observations. Climatic Change 101, 169-199.

Camuffo D., Jones P., 2002. Improved understanding of past climatic variability from early daily. European instrumental sources. Kluwer, Dordrecht, Germany.

Cohen L., 1995. Time frequency analysis: theory and application. Prentice Hall, Englewood Cliffs, NJ, USA.

Datig M., Schlurmann T., 2004. Performance and limitations of the Hilbert-Huang Transformation (HHT) with an application to irregular water waves. Ocean Engineering 31, 1783-1834.

Derham W., 1733-1734. An abstract of the Meteorological Diaries, communicated to the Royal Society, with re-marks upon them, by W. Derham, D. D. Canon of Windsor, F. R. S. [Vide Part III. In Transact. No 433.] Part IV. *Philosophical Transactions (1683-1775)* 38, 405-412.

Diodato N., Bellocchi G., 2010. Storminess and environmental changes in the Mediterranean Central Area. Earth Interactions 14, 1-16.

Diodato N., Bellocchi G., Bertolin C., Camuffo D., 2010. Multiscale regression model to infer historical temperatures in a central Mediterranean sub-regional area. Climate of the Past Discussion 6, 2625-2649.

Enzi S., Camuffo D., 1991. Effect of the global warming in the Southern: environmental history reconstruction in the Medieval Optimum climatic. In: 4°*Workshop Progetto Strategico Clima Ambiente e Territorio nel Mezzogiorno*, CNR Proceedings, Guerrini A., Piccione V., Antonelli C. (eds.), Vol. I , pp. 7-72 (in Italian).

Gather U., Fried R., Lanius V., 2006. Robust detail-preserving signal extraction. In: *Handbook of Time Series Analysis*, Schelter B., Winterhalder M., Timmer J. (eds.), Wiley-VCH VerlagGmbH & Co. KgaA, Weinheim, Germany; 131-157.

Giorgi F., Lionello P., 2008. Climate change projections for the Mediterranean region. Global and Planetary Change 63, 90-104.

Huang N.E., Attoh-Okine N., 2006. Hilbert Huang Transform in engineering. CRC Press, Boca Raton, Fl, USA.

Huang N.E., Shen Z., Long S.R., 1999. A new view of nonlinear water waves: the Hilbert spectrum. Annual Review of Fluid Mechanics 31, 417-457.

Huang N.E., Shen Z., Long S.R., Wu M.C., Shih E.H., Zheng Q., Tung C.C., Liu H.H., 1998. The empirical mode decomposition method and the Hilbert spectrum for non-stationary time series analysis. Proceedings of the Royal Society of London A 454, 903–995.

Ingad, U., 2009. Noise reduction analysis. Jones and Barlett Publishers, London, United Kingdom.

Kawamura A., McKerchar A.I., Spigel R.H., Jinno K., 1998. Chaotic characteristics of the Southern Oscillation Index time series. Journal of Hydrology 204, 168-181.

Knutti R., Allen M.R., Friedlingstein P., Gregory J.M., Hegerl G.C., Meehl G.A., Meinshausen M., Murphy J.M., Plattner G.-K., Raper S.C.B., Stocker T.F., Stott P.A., Teng T., Wigley T.M.L., 2008. A review of uncertainties in global temperature projections over the twenty-first century. Journal of Climate 21, 2651-2663.

Kollengodu-Subramanian S., Srinivasan B., Zhao J., Rengaswamy R., McKenna G.B., 2011. Application of empirical mode decomposition in the field of polymer physics. Polymer Physics 49, 277-290.

Luterbacher J., Dietrich D., Xoplaki E., Grosjean M., Wanner H., 2004. European seasonal and annual temperature variability, trends and extremes since 1500. Science 303, 1499-1503.

Mallat S., 1999. Wavelet tour of signal processing, 2nd edition. Academic Press, San Diego, CA, USA.

Mazzarella A., 2009. Sun-climate linkage now confirmed. Energy & Environment 20, 121-128.

McWilliams J.C., 2007. Irreducible imprecision in atmospheric and oceanic simulations. Proceedings of National Academy of Science 104, 8709-8713.

Moss R.H., Edmonds J.A., Hibbard K.A., Manning R.M., Rose S.K., van Vuuren D.P., Carter T.R., Emori S., Kainuma M., Kram T., Meehl G.A., Mitchell J.F.B., Nakicenovic N., Riahi K., Smith S.J., Stouffer R.J., Thomson A.M., Weyant J.P., Wilbanks T.J., 2010. The next generation of scenarios for climate change research and assessment. Nature 463, 747-756.

Nicolis C., Nicolis G., 1986. Reconstruction of the dynamics of the climatic system from time-series data. Proceedings of National Academy of Science 83, 536-540.

Nikovski D., Ramachandran G., 2009. Memory-based modeling of seasonality for prediction of climatic time series. Lecture Notes in Computer Science 5632, 734-748.

Ott H., 1988. Noise reduction techniques in electronic systems, 2nd edition. John Wiley & Sons, Ney York, NY, USA.

Salisbury J.I., Wimbush M., 2002. Using modern time series analysis techniques to predict ENSO events from the SOI time series. Nonlinear Processes in Geophysics 9, 341-345.

Singleton F., 2010. What limits forecast accuracy? http://weather.mailasail.com/Franks-Weather/Forecast-Accuracy-Limitations.

Smith S.W., 1999. The scientist and engineer's guide to digital signal processing. California Technical Publishing, San Diego, Ca, USA.

Stepanek P., 2007. AnClim - software for time series analysis (for Windows). Department of Geography, Faculty of Natural Sciences, Masaryk University, Brno, Czech Republic (http://www.climahom.eu/AnClim.html).

Stott P.A., Gillett N.P., Hegerl G.C., Karoly D.J., Stone D.A., Zhang X., Zwiers F., 2010. Detection and attribution of climate change: a regional perspective. Interdisciplinary Reviews: Climate Change 1, 192-211.

Viola F.M., Paiva S.L.D., Savi M.A., 2010. Analysis of the global warming dynamics from temperature time series. Ecological Modelling 22, 1964-1978.

Weber S.L., 2010. The utility of Earth system models of intermediate complexity (EMICs). Interdisciplinary Reviews: Climate Change 1, 243-252.

Wigley TML., 1992. Future climate of the Mediterranean Basin with particular emphasis in changes in precipitation. In Climate change in the Mediterranean, Jeftic L, Milliman JD, Sestini G (eds), Arnold, London, United Kingdom, 15-44.

Wu Z., Huang N.E., 2008. Ensemble Empirical Mode Decomposition: a noise-assisted data analysis method. Advances in Adaptive Data Analysis 1, 1-41.