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Analysis of the global warming dynamics from temperature time series

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ABSTRACT

Global warming is the observed increase of the average temperature of the Earth. The primary cause of this phenomenon is the release of the greenhouse gases by burning of fossil fuels, land cleaning, agriculture, among others, leading to the increase of the so-called greenhouse effect. An approach to deal with this important problem is the time series analysis. In this regard, different techniques can be applied to evaluate the global warming dynamics. This kind of analysis allows one to make better predictions increasing our comprehension of the phenomenon. This article applies nonlinear tools to analyze temperature time series establishing state space reconstruction and prediction. Since noise contamination is unavoidable in data acquisition, it is important to employ robust techniques. The method of delay coordinates is employed for state space reconstruction and delay parameters are evaluated using the method of average mutual information and the method of false nearest neighbors. Afterwards, the simple nonlinear prediction method is employed to estimate temperatures of the future. Temperature time series from different places of the planet are used. Initially, the approach is verified considering known parts of the time series and afterwards, results are extrapolated for future values estimating temperature until 2028. Results show that these techniques are interesting to estimate temperature time history, presenting coherent estimations.

1. Introduction

The observation of climate system allows one to identify two distinct phenomena related to the system evolution: climate change, usually related to human activities, and climate variability, usually associated with natural causes (UNFCCC, 1992).

Climate variability denotes deviations of climate conditions over a period of time due to natural phenomena (WMO, 2010). There are many examples of these anomalies as the Interdecadal Pacific Oscillation (IPO) that causes decadal changes in climate averages; the El Niño-La Ninã Southern Oscillation (ENSO) that causes much variability throughout many tropical and subtropical regions; and the North Atlantic Oscillation (NAO) that provides climate perturbations over Europe and Northern Africa (Salinger, 2005). Climate change, on the other hand, is usually associated with anthropogenic causes and is associated with permanent changes.

Global warming is one aspect of climate change and, actually, is induced either by natural processes or by human activities. In brief, global warming is the observed increase in the average temperature of the Earths' atmosphere and oceans. The primary cause of this phenomenon is the release of greenhouse gases by the burning of fossil fuels and the large-scale deforestation, leading to the increase of the so-called greenhouse effect that arises as a consequence of the unbalanced presence of greenhouse gases in the atmosphere. Among others, the greenhouse gases are the carbon dioxide, the methane and the nitrous oxide (Houghton, 2005).

From industrial revolution on, the amount of greenhouse gases in the atmosphere has significantly increased. Based on *Intergovernmental Panel on Climate Change* data (IPCC, 2007), the carbon dioxide has increased by more than 30% and is still increasing at a rate of 0.4% per year. Other greenhouse gases are also increasing and there are evidences pointing to the anthropogenic cause of this phenomenon. During the 20th century, the Earth's surface mean temperature has increased approximately 0.4–0.8 °C. Most of this increase has occurred in two periods: from 1910 to 1945 (0.14 °C/decade) and since 1976 (0.17 °C/decade) (Salinger, 2005). The consequences of the global warming are unpredictable; however, one could mention climate sensitivity and other changes related to the frequency and intensity of extreme weather events (IPCC, 2001).

Climate change analysis is important in order to define different scenarios whose knowledge is important for several purposes. In the same way, global warming analysis is important to establish models that can predict the evolution of greenhouse gases and Earth's temperature. Besides, it is important to evaluate the consequences of the effects of these variations in global balance and in life. Literature presents several efforts dealing with this kind

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of analysis. Concerning modeling effort one could establish the following classification (Alexiadis, 2007): general circulation models (GCMs); model-based methods (MBMs) or empirical models; planet's dynamics models (PDMs). Moreover, we can highlight the existence of models built upon time series analysis (TSA). Regarding more general dynamical systems, it is possible to present a different classification that, actually, is in agreement with the previous one (Aguirre, 2007; Aguirre and Lettelier, 2009): white-box models, based on physical argues; black-box models, based on time series; and gray-box models that mixture both ideas.

GCMs consider physical aspects of system dynamics including conservation of mass, energy and momentum. An important characteristic of this kind of modeling is the high computational effort related to simulations (Friedlingstein et al., 2003; Cox et al., 2000; Joos et al., 2001). Houghton (2005) presented an overview of models based on physical principles. Regional climate models (RCMs) constitute an alternative approach based on GCMs (Alpert et al., 2008; Kueppers et al., 2008). Among other alternative approaches, it should be highlighted models that try to reduce uncertainties using statistical considerations (Ghila et al., 2008; Lopez et al., 2006).

MBMs use some empirical observations and/or statistical tools from experimental time series and therefore, do not deal with system's physics directly (Kaufmann and Stern, 1997; Loehle, 2004; Krivova and Solanki, 2004). Stringham et al. (2003) presented a review of conceptual models pointing out the inconsistencies in the application of non-equilibrium ecology concepts. Young and Ratto (2009) proposed a unified approach to the modeling of environmental systems by considering information from analysis of real data. The idea was to connect MBM and GCM approaches.

PDM are based on a simplified description of the system dynamics and falls between the previous two categories (Moore, 2007; Kay et al., 2009). Daisyworld, originally proposed by Lovelock (1992), is a prototype of this kind of approach. In brief, daisyworld establishes the self-regulation of the planetary system representing life by daisy populations while the environment is represented by temperature. The daisyworld is an archetypal of Earth and is able to describe the global regulation that can emerge from the interaction between life and environment (Lenton and Lovelock, 2000, 2001).

Finally, the time series analysis tries to build a model from experimental data. Alexiadis (2007) considered time series analysis based on control theory, using system identification techniques to determine the transfer functions that approximate the system dynamics. Qin et al. (2008) employed the continuous wavelet transform technique to analyze water vapor and carbon dioxide fluxes in agricultural lands investigating global warming potentials. Capilla (2008) employed a local polynomial regression fitting and wavelet methods in order to identify trends in a Mediterranean urban area. Rybski and Bundea (2009) employed the detrended fluctuation analysis to quantify underlying trends in long-term correlated records. Temperature time series are of concern using different tools for the analysis.

Subba and Antunes (2003) presented a review of space-time autoregressive moving average (STARMA) models. The STARMA forecast performance is compared with ARMA models, using real data. Afterward, Antunes and Subba (2006) proposed statistical tests comparing space-time autoregressive processes and multivariate autoregressive processes. Koçak et al. (2004) employed nonlinear techniques for time series prediction using a polynomial approximation. Romilly (2005) employed the autoregressive-integrated-moving average model (ARIMA) together with more recent developments to analyze global mean temperature dataset. Founda et al. (2004) employed statistical methods for temperature time series observing trends and extreme events in Athens seasons from 1897 to 2001. Grieser et al. (2002) used statistical methods to decompose temperature time series into a sum of trend, annual cycles, episodic and harmonic components, extreme events and noise.

Literature also presents efforts related to several aspects of ecological modeling. Among others, one can cite Urban (2005) that discussed the multi-scale aspects related to the modeling of ecological systems. Kettleborough et al. (2007) described a method to estimate the uncertainty in global mean temperature change. Jacob and Winner (2009) described the impact of climate change on air quality.

This contribution deals with time series analysis related to the global warming dynamics. The idea is to model the system dynamics from temperature time series that is considered as a representative variable of the system. Since noise contamination is unavoidable in data acquisition, it is important to employ robust techniques (Franca and Savi, 2001, 2003). In this regard, the method of delay coordinates is employed for the state space reconstruction and delay parameters, time delay and embedding dimension, are respectively evaluated using the method of average mutual information and the method of false nearest neighbors. The simple nonlinear prediction is employed to model the system dynamics evaluating the prediction of future values. This approach is verified by considering known parts of the time series and afterwards, results are extrapolated for future values. The verification process is of special interest since time series is contaminated by noise being related to a system with high dimension characteristics that make the application of nonlinear techniques a difficult task. Nonlinear time series analysis employs the TISEAN package (Hegger et al., 1999). Time series from different locations of the world are investigated in order to characterize the global temperature. Specifically, eight time series are of concern: Montreal (Canada), Los Angeles (USA), Rio de Janeiro (Brazil), London (United Kingdom), Johannesburg (South Africa), Beijing (China), Tokyo (Japan) and Albany (Australia).

This paper is organized as follows. After the introduction, a brief discussion about global warming is carried out showing some temperature time series measured in different weather stations. Nonlinear tools related to time series analysis are then presented discussing state space reconstruction and prediction techniques. The application of nonlinear time series analysis is discussed in the next section considering different temperature time series of the Earth. Basically, prediction analysis is split into two parts: model verification and future forecast. In the first part, it is shown that prediction techniques are able to capture the general behavior of time series from known time series. Afterwards, future forecast is carried out estimating temperature until 2028. Conclusions are then presented at the end of the paper.

2. Global warming

Climate system has an inherent complexity due to different kinds of phenomena involved. The equilibrium of this system is a consequence of different aspects related to atmosphere, oceans, biosphere, among others, and the sun activity provides the driving force for this system. In brief, greenhouse gases may be absorbed by the natural systems which are represented by the carbon cycle. Oceans, rivers and forests are essential for this process. The human influence tends to break this balance either by increasing the amount of gases or by decreasing the natural capacity to absorb them due to deforestation and pollution (IPCC, 2007).

The Earth's heating mechanism may be understood as the balance between the radiation energy from the sun and the thermal radiation from the Earth that is radiated out to space. The excessive presence of greenhouse gases tends to break this balance since they are transparent to the sun short wave radiation, however, they absorb some of the longer infrared radiation emitted from the Earth.

Fig. 1. Weather stations.

Therefore, the increase amounts of these gases introduce a difficulty related to the thermal balance, increasing the temperature of the Earth.

The global warming is a spatiotemporal phenomenon, however, the analysis of temporal aspects of this system can provide important information for its comprehension. All over the world, there are numerous measurements concerning temperature time series. The National Oceanic and Atmospheric Administration (NOAA) has 9000 weather stations with measurements since 1929, but data from 1973 are more complete and include a great number of stations (NOAA, 2006).

In order to give an idea concerning the global warming phenomenon, eight different temperature time series from 1989 to 2008 are considered: Montreal (Canada), Los Angeles (USA), Rio de Janeiro (Brazil), London (United Kingdom), Johannesburg (South Africa), Beijing (China), Tokyo (Japan) and Albany (Australia). Fig. 1 presents the localization of the weather stations while Table 1 shows information about source of data. In Table 1, "USAF" means US Air Force station number.

Fig. 2 shows temperature time series and their linear fit showing the tendency of the temperature evolution. It should be observed that these time series present different patterns. The linear match shows an increase of temperature in Montreal (+2.22 °C), London (+0.64 °C), Johannesburg (+1.18 °C), Beijing (+0.10 °C), Tokyo (+0.95 °C) and Albany (+0.11 °C). Nevertheless, there is a decrease of temperature in Los Angeles (−0.09) and Rio de Janeiro (−0.55). Another important characteristic of these series is related to their range. Each one has minimum and maximum values that depend on climatic aspects of its geographical region.

3. Time series analysis

The basic idea of the state space reconstruction is that a signal contains information about unobserved state variables (Savi, 2006). Therefore, a scalar time series, S_n, may be used to construct a vector time series that is equivalent to the original dynamics from a topological point of view. The state space reconstruction needs to form a coordinate system to capture the structure of orbits in state space, which could be done using lagged variables, $S_{n+\tau}$, where τ is the time delay. Then, it is possible to use a collection of time delays to create a vector in a D_e-dimensional space:

$$U(t) = \{S_n, S_{n+\tau}, \ldots, S_{n+(D_e-1)\tau}\}^T \tag{1}$$

The application of this approach is associated with the determination of delay parameters, time delay, τ, and embedding dimension, D_e. The mutual information method (Fraser and Swinney, 1986) is a good alternative to evaluate the time delay, τ. The determination of embedding dimension, D_e, on the other hand, may be evaluated from the method of the false nearest neighbors (Kennel et al., 1992). This reconstructed space can be used for the forecast and the simple nonlinear prediction is a good alternative for this aim. Fig. 3 presents the sequence of the time series analysis employed in this work. The forthcoming sections present a brief discussion of the employed methods.

3.1. Method of average mutual information

The idea for the determination of proper time delay for state space reconstruction is to obtain lagged variables as most independent as possible. Fraser and Swinney (1986) established that the time delay τ is related to the first local minimum of the average mutual information function $I(\tau)$, which is defined as follows:

$$I(\tau) = \sum_{n=1}^{N-\tau} \Gamma(S_n, S_{n+\tau}) \log_2 \left[\frac{\Gamma(S_n, S_{n+\tau})}{\Gamma(S_n)\Gamma(S_{n+\tau})} \right] \tag{2}$$

where $\Gamma(S_n)$ is the probability of the measure S_n, $\Gamma(S_{n+\tau})$ is the probability of the measure $S_{n+\tau}$, and $\Gamma(S_n, S_{n+\tau})$ is the joint proba-

Table 1
Source of data.

USAF	Station name	Latitude	Longitude	Elevation (.1M)
716270	Montreal	+45467	−73750	+00299
722950	Los Angeles Intl. Arpt.	+33938	−118406	+00994
837550	Rio de Janeiro Aero	−22900	−043167	+00030
037720	London/Heathrow	+51483	−000450	+00250
683680	Johannesburg Intl.	−26150	+028233	+17200
545110	Beijing	+39933	+116283	+00550
476620	Tokyo	+35683	+139767	+00360
948020	Albany airport	−34933	+117800	+00690

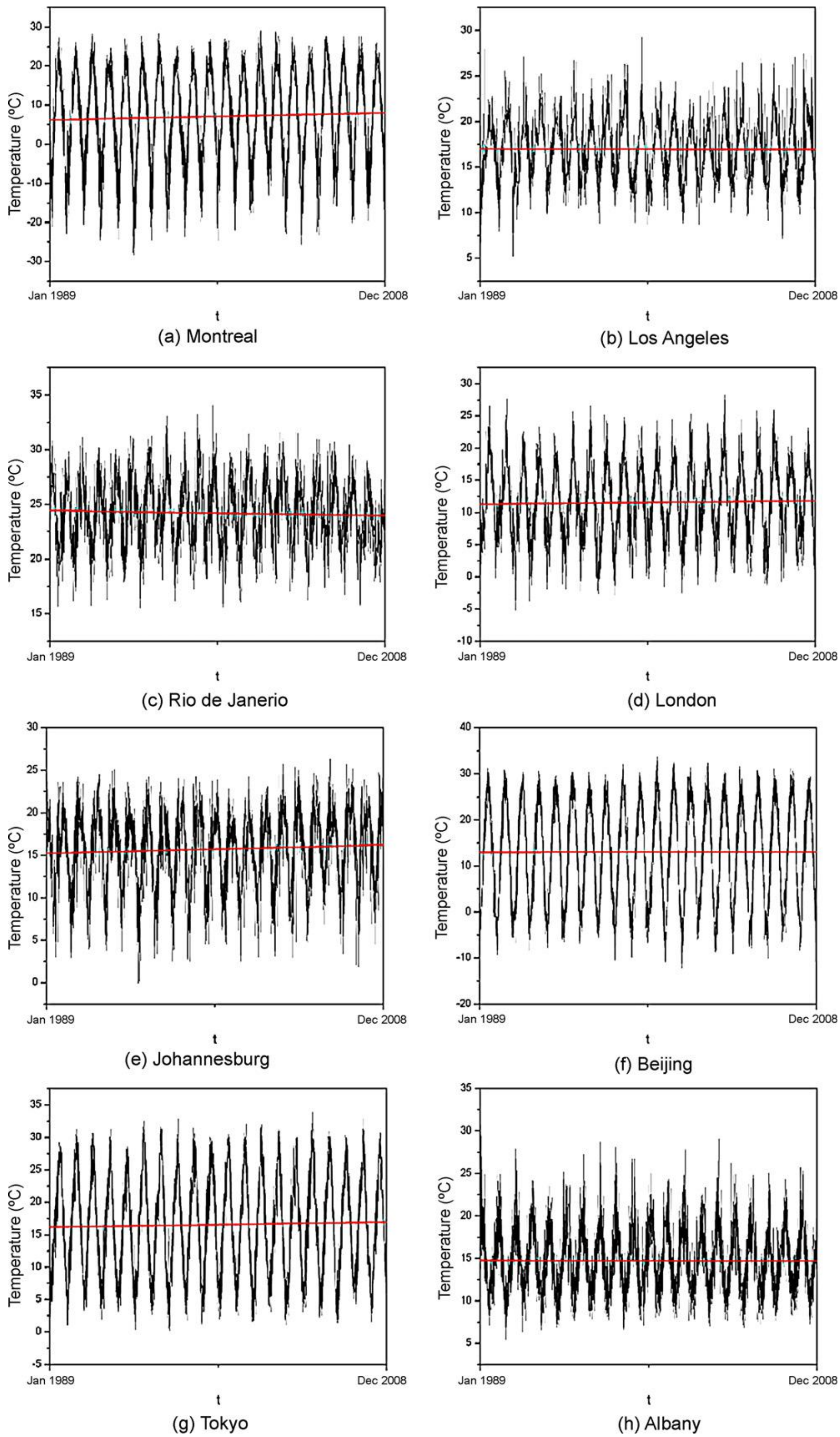

Fig. 2. Temperature time series and linear fit.

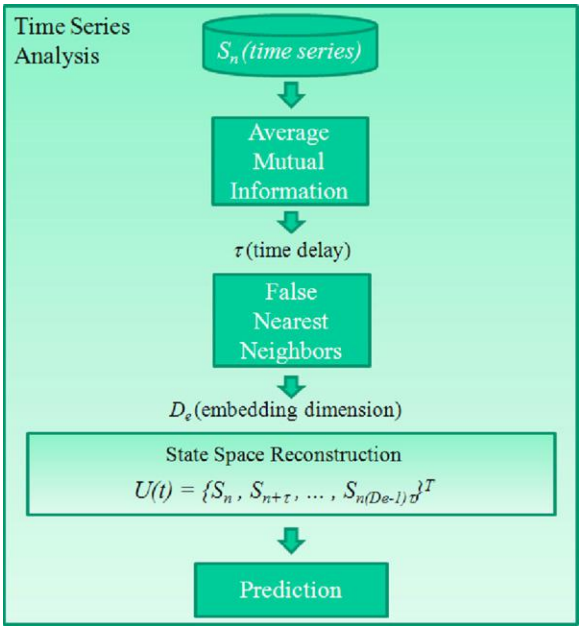

Fig. 3. Schematic of time series analysis.

bility of the measure of S_n and $S_{n+\tau}$. When the measures S_n and $S_{n+\tau}$ are completely independent, $I(\tau) = 0$. On the other hand, when S_n and $S_{n+\tau}$ are equal, $I(\tau)$ is maximum. Therefore, the analysis of the $I(\tau)$ curve allows one to determine the best time delay to be used in the state space reconstruction.

3.2. Method of the false nearest neighbors

The method of the false nearest neighbors establishes that in an embedding dimension that is too small to unfold the attractor, not all points that lie close to one another will be neighbors because of the dynamics. Some will actually be far from each other and simply appear as neighbors because the geometric structure of the attractor has been projected down onto a smaller space (Kennel et al., 1992). In order to use the method of the false nearest neighbors, a D-dimensional space is considered where the point U_n has r-th nearest neighbors, U_n^r. The square of the Euclidean distance between these points is:

$$r_D^2(n, r) = \sum_{k=0}^{D-1} \left[S_{n+k\tau} - S_{n+k\tau}^r\right]^2 \qquad (3)$$

Now, going from dimension D to $D+1$ by time delay, there is a new coordinate system and, as a consequence, a new distance between U_n and U_n^r. When these distances change from one dimension to another, these are false neighbors. A proper space dimension may be obtained when there are no false neighbors after a dimension increase.

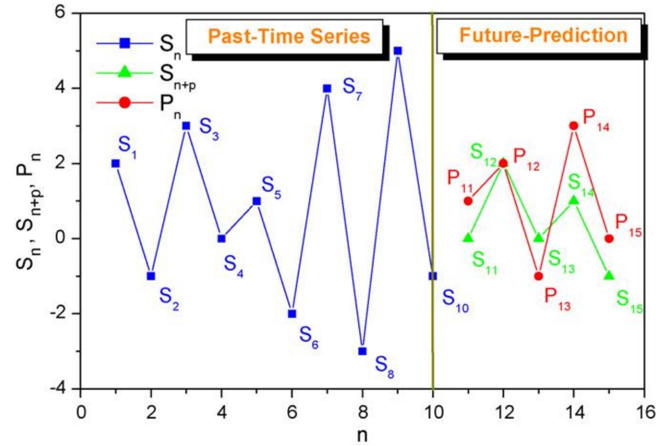

Fig. 4. Time series prediction.

3.3. Prediction

Prediction is a particular application related to system modeling that uses a known time series called past, $S_n, n = 1, \ldots, N$ to estimate future values, called future, $S_n, n = N+1, \ldots, N+p$. This model establishes a way to estimate future series: $P_{N+1}, P_{N+2}, \ldots, P_{N+p}$. Fig. 4 shows a schematic plot related to the prediction problem. A verification procedure can be performed using known parts of the series and establishing a comparison between estimated values with future values associated with the original series (Savi, 2006; Fraser and Swinney, 1986; Kennel et al., 1992; Pinto and Savi, 2003). In general, prediction techniques may be classified in linear and nonlinear methods or, alternatively, local and global methods. An overview of the main aspects related to nonlinear time series analysis and prediction is provided in references (Aguirre, 2007; Pinto and Savi, 2003; Kantz and Schreiber, 1997; Abarbanel, 1995; Casdagli, 1989; Schreiber, 1999; Weigend and Gershenfeld, 1994).

An alternative to the time series forecast is the simple nonlinear prediction that is based on the state space reconstruction. After the reconstruction, the prediction of a time instant Δn ($\Delta n = 1, .., p$) ahead N, is done by defining a parameter ε that establishes the size of the neighborhood $V_\varepsilon(U_N)$ around point U_N in the reconstructed space. All points inside this neighborhood are used for the prediction. Therefore, all points U_n closer than ε to $U_N (U_n \in V_\varepsilon(U_N))$ are employed for the prediction $P_{N+\Delta n}$. Different approaches can be employed to estimate the prediction from these points. Here the prediction is calculated from the average of the individual predictions $S_{n+\Delta n}$ as follows:

$$P_{N+\Delta n} = \frac{1}{\left|V_\varepsilon(U_N)\right|} \sum_{U_n \in V_\varepsilon(U_N)} S_{n+\Delta n} \qquad (4)$$

where $\left|V_\varepsilon(U_N)\right|$ denotes the number of elements of the neighborhood $V_\varepsilon(U_N)$. More details about this procedure could be found in

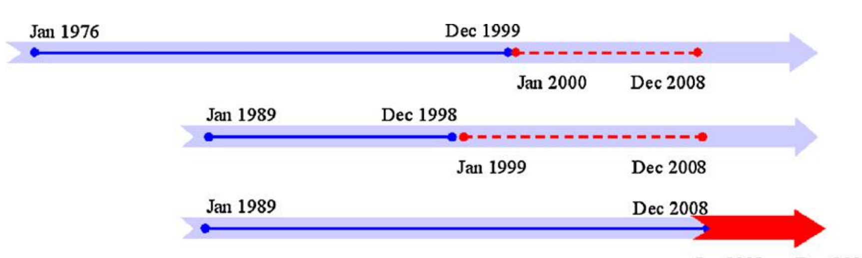

Fig. 5. Analyzed time series (solid line) and their prediction periods (dashed line).

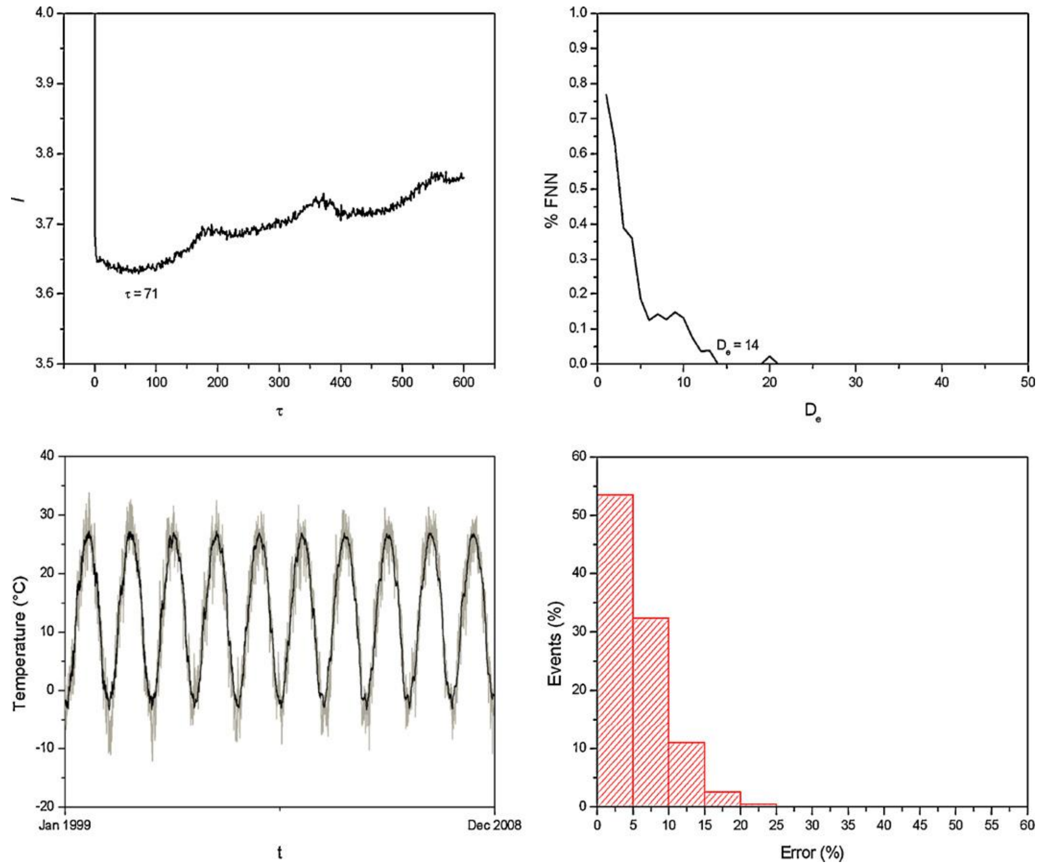

Fig. 6. Beijing (China) prediction, time series from 1999 to 2008. Delay parameters analysis; comparison between time series (light line) and prediction (dark line); error analysis.

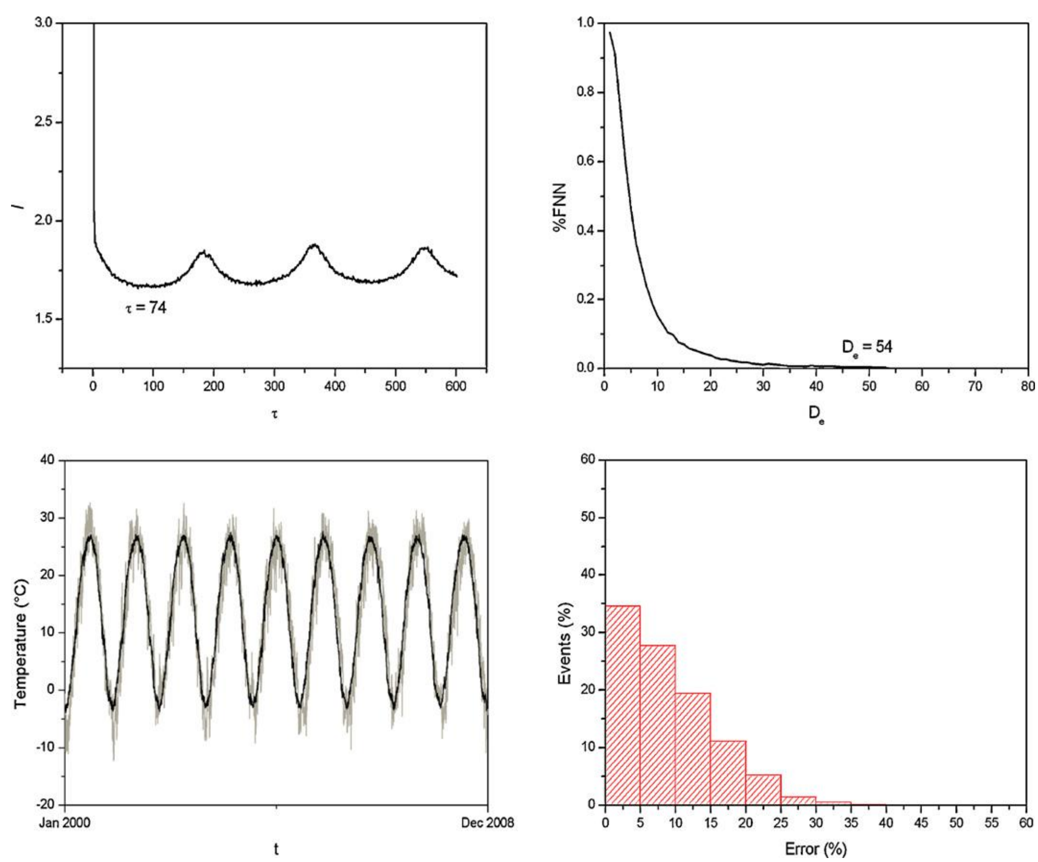

Fig. 7. Beijing (China) prediction, time series from 2000 to 2008. Delay parameters analysis; comparison between time series (light line) and prediction (dark line); error analysis.

Kantz and Schreiber (1997), Casdagli (1989), and Pinto and Savi (2003).

4. Analysis of temperature time series of the earth

The analysis of temperature time series of the Earth is carried out in this section. Initially, a verification of the model is of concern considering different situations defined by distinct parts of each series. Afterwards, results are extrapolated for the prediction of future values of the series. The idea of the verification is to use time series from 1989 to 1998 (10 years) performing the prediction from 1999 to 2008 (10 years). Since the period from 1999 to 2008 is known, it is possible to verify the capability of the procedure to perform the forecast. The importance of the number of data points is evaluated by considering a larger time series from 1976 to 1999 (24 years) performing the prediction from 2000 to 2008 (9 years). Filtering procedures are also evaluated by considering the moving average filter. This filter is used to smooth time series being defined as follows:

$$y_n = \frac{1}{m} \sum_{k=-(m-1)/2}^{(m-1)/2} S_{n+k} \tag{5}$$

where m is the factor (days) of the average filter used in the calculation. The factor used for this work is 7 days. After this verification, a different analysis is performed by considering a series from 1989 to 2008 (20 years) in order to predict future values from 2009 to 2028 (20 years). It should be pointed out that some series has missing data points and we do not perform a special treatment for this series. Fig. 5 shows a time line of the model verification and the future forecast.

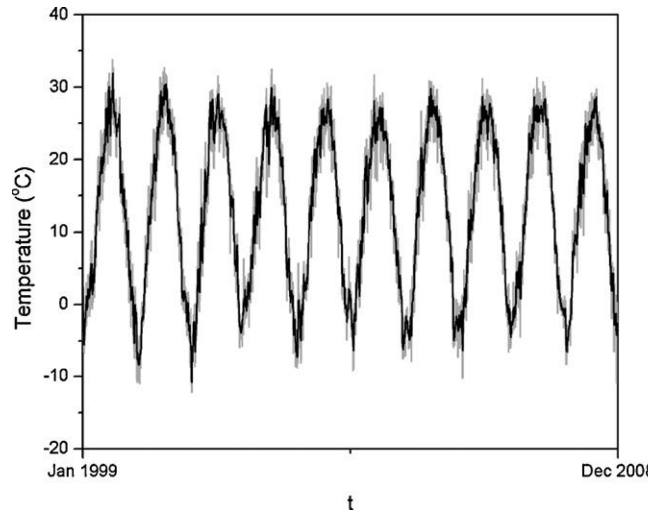

Fig. 8. Beijing (China), time series from 1999 to 2008. Original (light line) and filtered (dark line) time series.

In order to establish the model verification, predicted results are compared with time series and two errors are defined: the average error and the daily error. The average error is defined as follows:

$$\bar{E} = \frac{\left|\bar{S} - \bar{P}\right|}{\bar{S}} \tag{6}$$

where $\bar{S}$ is the average of the time series and $\bar{P}$ is the average of the prediction evaluated during the same period, both defined by considering Celsius scale. On the other hand, the daily error is defined

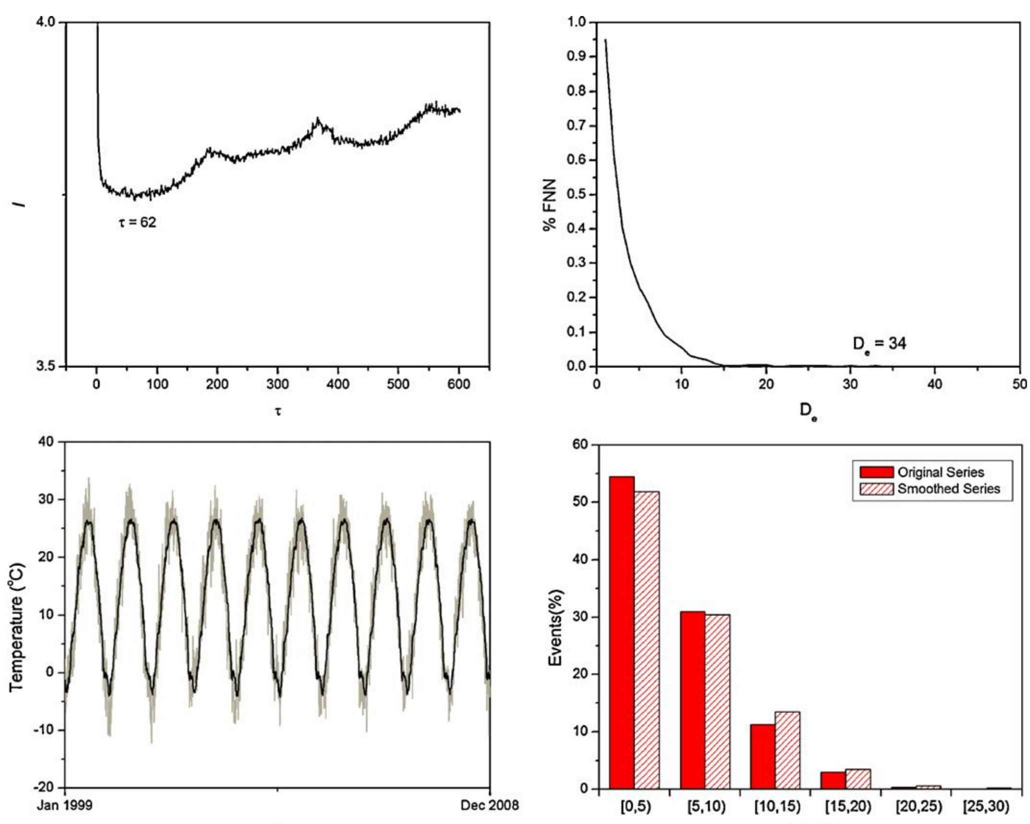

Fig. 9. Beijing (China) prediction, time series from 1999 to 2008. Delay parameters analysis; comparison between time series (light line) and prediction (dark line); error analysis.

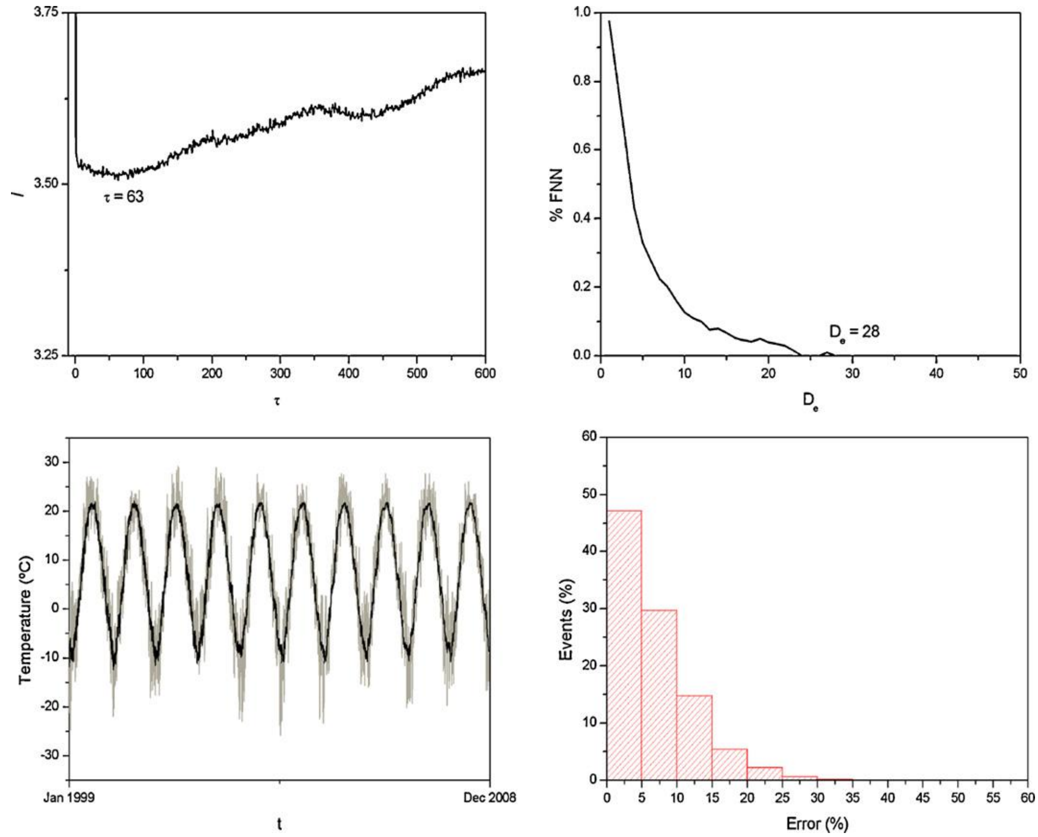

Fig. 10. Montreal (Canada) prediction. Delay parameters analysis; comparison between time series (light line) and prediction (dark line); error analysis.

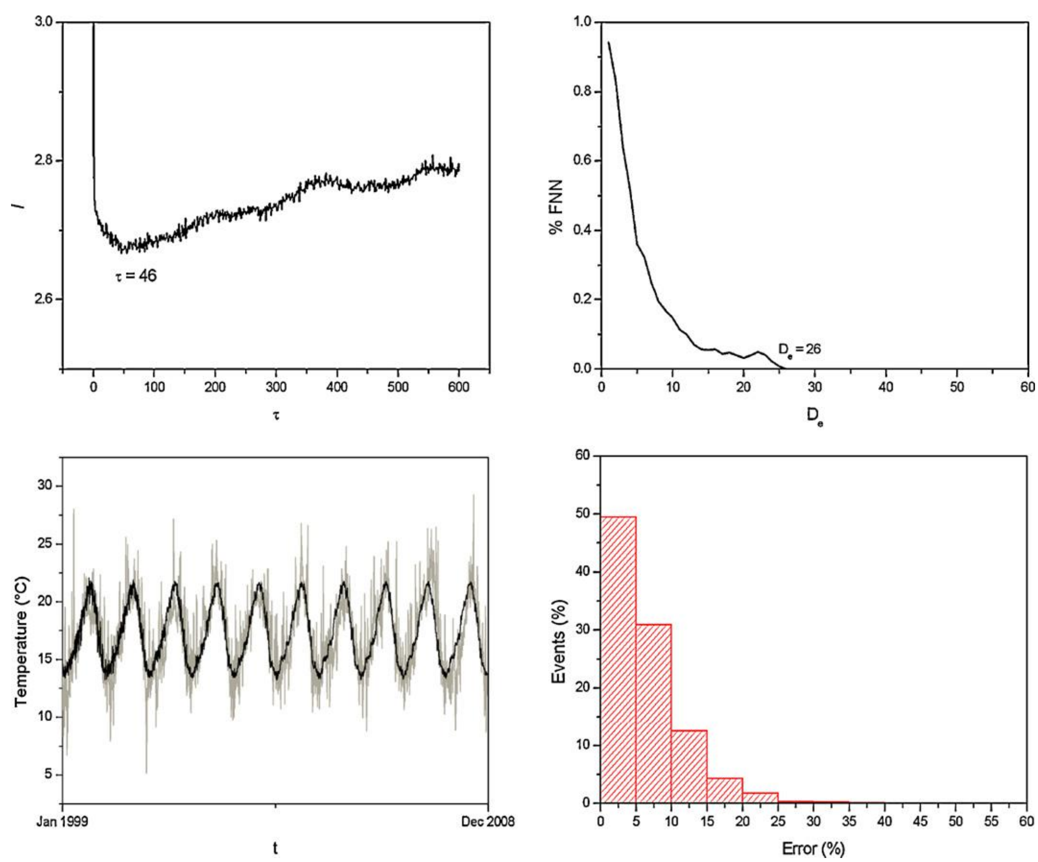

Fig. 11. Los Angeles (USA) prediction. Delay parameters; comparison between time series (light line) and prediction (dark line), from 1999 to 2008; error analysis.

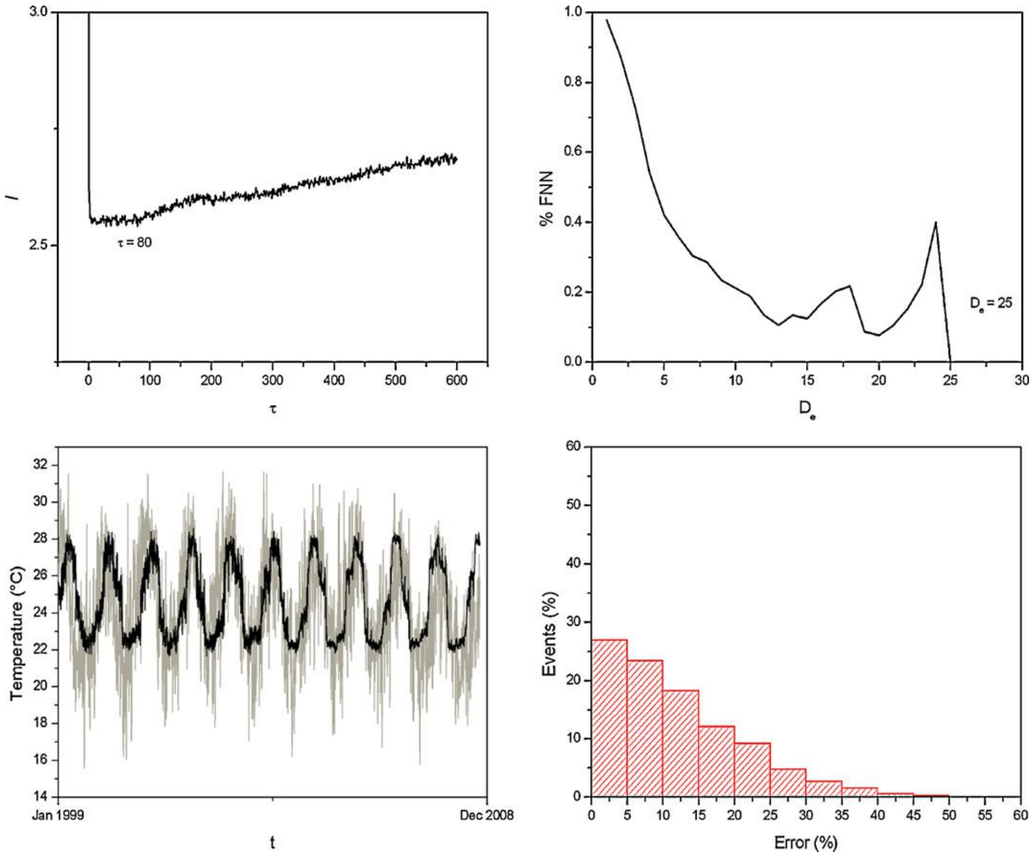

Fig. 12. Rio de Janeiro (Brazil) prediction. Delay parameters; comparison between time series (light line) and prediction (dark line), from 1999 to 2008; error analysis.

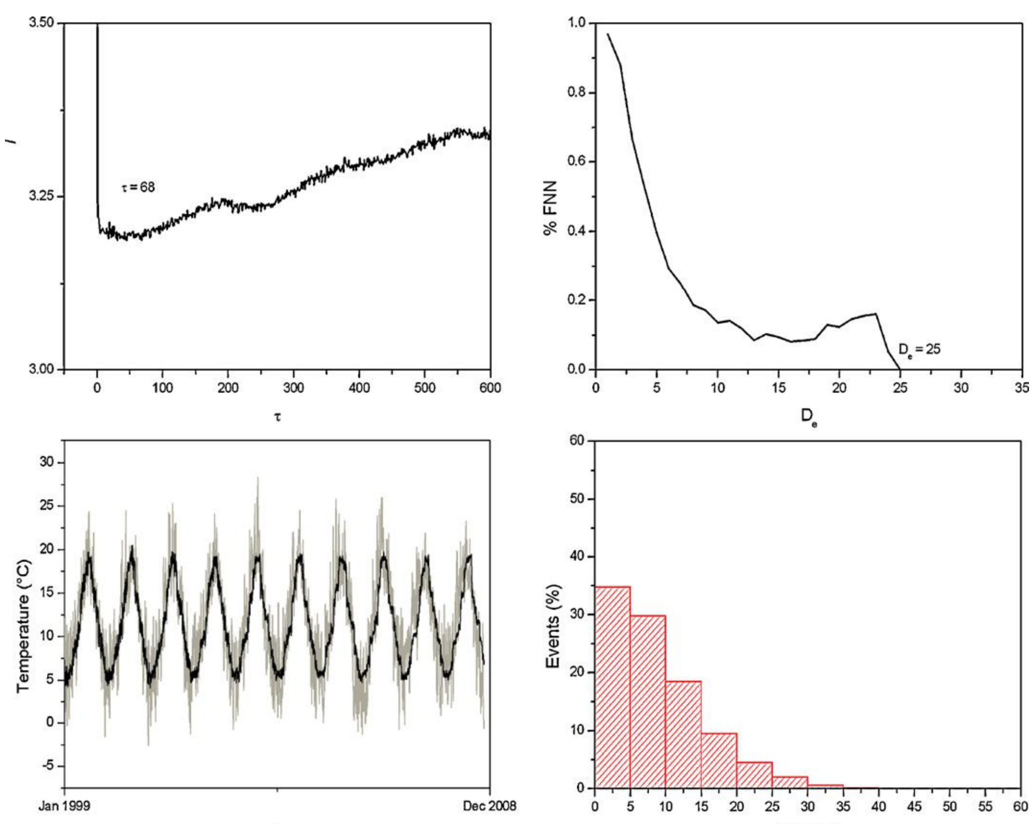

Fig. 13. London (UK) prediction. Delay parameters; comparison between time series (light line) and prediction (dark line), from 1999 to 2008; error analysis.

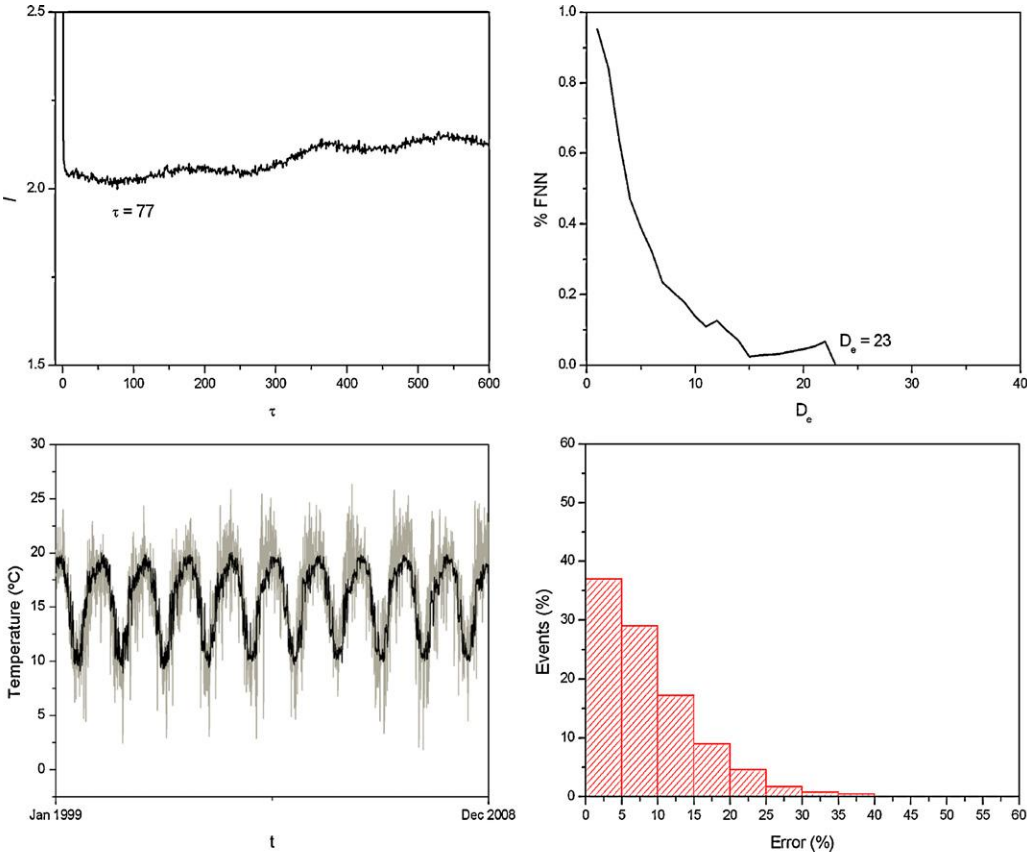

Fig. 14. Johannesburg (South Africa) prediction. Delay parameters; comparison between time series (light line) and prediction (dark line), from 1999 to 2008; error analysis.

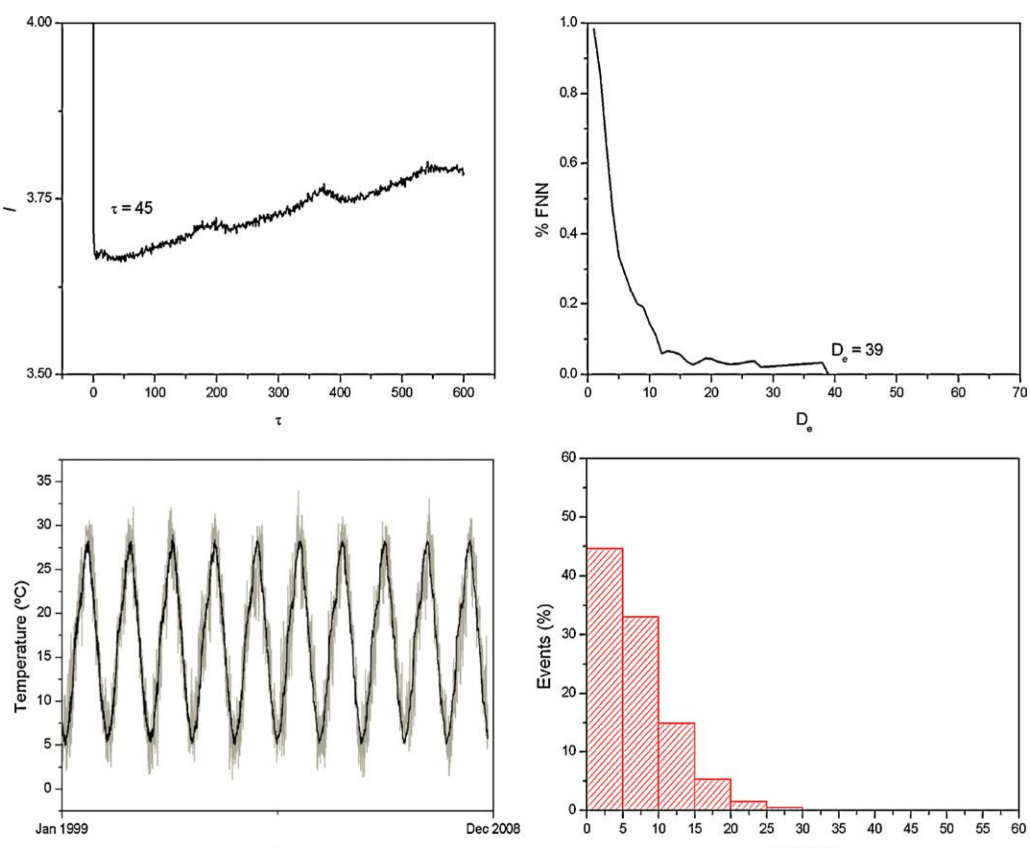

Fig. 15. Tokyo (Japan) prediction. Delay parameters; comparison between time series (light line) and prediction (dark line), from 1999 to 2008; error analysis.

Table 2
Summary of the verification procedure.

Time series	Data points	T	D_e	Average of time series (°C)	Average of prediction (°C)	Difference (%)
Montreal (Canada)	3652	63	28	7.57	7.17	5.28
Los Angeles (USA)	3651	46	26	17.11	17.22	0.64
Rio de Janeiro (Brazil)	3444	80	25	24.14	24.60	1.91
London (UK)	3652	68	25	11.67	11.34	2.83
Johannesburg (South Africa)	3651	77	23	15.92	15.68	1.51
Beijing (China)	3652	71	14	12.99	13.08	0.69
Tokyo (Japan)	3651	45	39	16.69	16.48	1.26
Albany (Australia)	3646	61	24	14.78	14.60	1.22

by the expression:

$$E_n^D = \frac{|S_n - P_n|}{(T_{\max} - T_{\min})} \tag{7}$$

where $T_{\max}$ and $T_{\min}$ are, respectively, the maximum and minimum temperatures of the time series.

4.1. Model verification evaluating general aspects of the prediction

The model verification is performed by considering known values of the series in order to compare original and predicted values. Initially, time series from Beijing (China) is considered as the archetypal of the system dynamics evaluating the general aspects of the prediction and the number of data points treating two different situations: 1989–1998 (10 years) predicting from 1999 to 2008 (10 years); 1976–1999 (24 years) predicting from 2000 to 2008 (9 years). The influence of filtering process is also evaluated by considering smoothed time series to perform the forecast. Afterwards, other time series are treated considering the same procedure for series from 1989 to 1998 (10 years) predicting from 1999 to 2008 (10 years). These choices are based on the number of data points and the possibility to consider data without missing points.

Let us now consider a 10-year time series of Beijing (China) associated with a period from 1989 to 1998, representing 3652 data points. Delay parameters are analyzed in Fig. 6 (upper part) that presents average mutual information and false nearest neighbors analyses. This analysis indicates a time delay $\tau = 71$ defined by the first minimum of the information curve and embedding dimension $D_e = 14$, defined by a value where the system does not present false neighbors. These results are used to perform predictions from 1999 to 2008, representing 10 years. Fig. 6 (lower part) presents the original time series together with the prediction made by the simple nonlinear prediction and an error histogram that shows the distribution of events related to daily error between the series and the prediction. The forecast capture the general behavior of the time series, presenting average values of 12.99 °C for the time series and 13.08 °C for the prediction, which means a difference of 0.69%. Besides, the daily error analysis shows that the majority of predic-

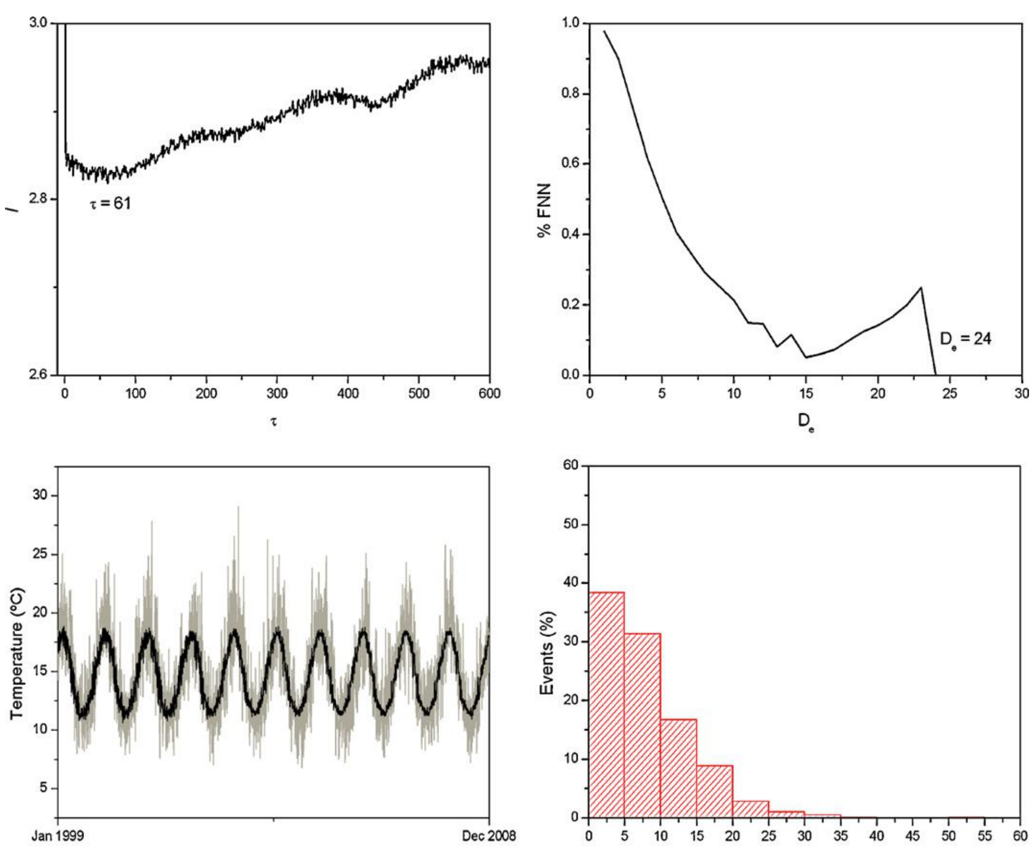

Fig. 16. Albany (Australia) prediction. Delay parameters; comparison between time series (light line) and prediction (dark line), from 1999 to 2008; error analysis.

tions have low errors. Note that 85% of points have errors less than 10%.

In order to evaluate the influence of the number of data points, a time series corresponding to 24 years with 8745 data points (from 1976 to 1999) is of concern. The analysis starts by evaluating delay parameters. Fig. 7 (upper part) presents average mutual information and false nearest neighbors analyses. From these, it is possible to conclude that time delay is $\tau = 74$ and embedding dimension is $D_e = 54$. It should be highlighted that this series has missing data that does not receive special treatment. Afterwards, simple nonlinear prediction is employed to model the series predicting future values from 2000 to 2008 (9 years), as shown in Fig. 7 (lower part). Results show a good agreement between the original and the predicted series and it is important to note that both series has average values that are very close (respectively, 12.98 °C and 12.97 °C representing a difference of 0.12%). Although this larger time series presents better results in terms of average, the histogram presents worst results.

The preceding analysis showed that time series from 1999 to 2008 (10 years) is able to capture the behavior of this series for forecast purposes. Therefore, this period is used for the analysis of the other series. Before this, we investigate the influence of filtering in time series analysis. Basically, the moving average filtering that smoothes time series is employed and, after that, state space reconstruction and prediction are performed. Fig. 8 presents original and filtered time series. Fig. 9 shows prediction analysis showing average mutual information and false nearest neighbors and forecast. From delay parameters analysis, it is possible to conclude that time delay is $\tau = 62$ and embedding dimension is $D_e = 34$. Note that time delay is basically the same and embedding dimension is reduced by the filtering. Afterwards, simple nonlinear prediction is employed to model the series predicting future values from 2000 to 2008 (9 years). Once again, results show a good agreement between the original and the predicted series. It is important to observe that results are basically the same of those without filtering which encourage us to develop the analysis from original time series, without filtering.

4.2. Model verification

The analysis of Beijing (China) showed that that time series from 1989 to 1998 (10 years) is able to capture the behavior of this series for forecast purposes. Moreover, results of filtered series are basically the same of those obtained without filtering. From now on, the same verification procedure employed for the Beijing (China) series is considered for the following time series: Montreal (Canada), Los Angeles (USA), Rio de Janeiro (Brazil), London (United Kingdom), Johannesburg (South Africa), Tokyo (Japan) and Albany (Australia). Essentially, it is considered series with 10 years (from 1989 to 1998) corresponding to approximately 3650 data points and filtering process are not considered. The analysis starts by evaluating delay parameters, presenting average mutual information and false nearest neighbors analyses. Afterwards, simple nonlinear prediction is employed to model the series predicting future values from 1999 to 2008 (10 years). This procedure is repeated for each time series and results are shown in Figs. 10–16 and each figure presents a set of four pictures: delay parameters analyses (average mutual information and false nearest neighbors curves); prediction analysis that includes the original time series together with the prediction made by the simple nonlinear prediction; and the error analysis that presents the error histogram that shows the distribution of events with the corresponding daily error between the time series and its prediction.

In order to organize results, let us summarize the list of figures and the corresponding time series: Montreal (Canada)—Fig. 10; Los Angeles (USA)—Fig. 11; Rio de Janeiro (Brazil)—Fig. 12; London (UK)—Fig. 13; Johannesburg (South Africa)—Fig. 14; Tokyo (Japan)—Fig. 15; Albany (Australia)—Fig. 16.

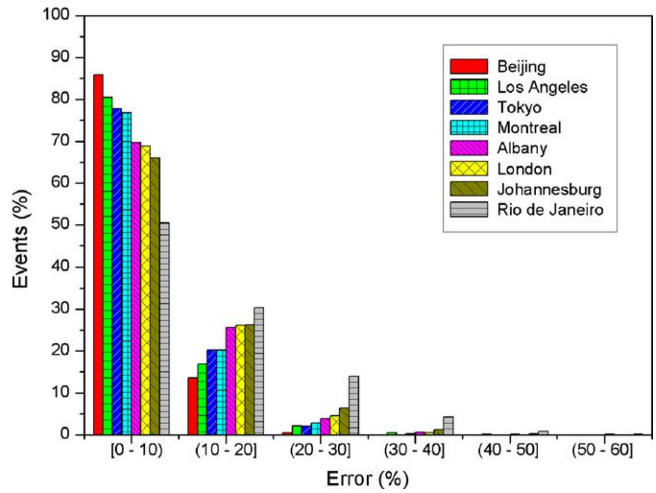

Fig. 17. Error analysis of the forecast.

In general, results show good agreement between the original and the predicted series and it is important to note that both series has average values that are very close. Table 2 summarizes the main results presenting the delay parameters and the average of the time series and the predicted values together with the error between them (including Beijing (China)). Results show that error related to average value varies from 0.64% to 5.28%. Moreover, histograms show that most of the prediction values have small daily errors presenting a tendency to be concentrated in errors less than 10%. Actually, the worst forecast presents 50% of the predictions with less than 10% while the best forecast presents 85% of the predictions with less than 10%. Fig. 17 summarizes these histograms giving a good idea of the general behavior. This analysis shows that prediction procedure is able to capture the general behavior of the time series, especially concerning the average values.

5. Forecast

Since the proposed procedure has captured the general behavior of the temperature evolution, we are encouraged to make predictions of the future. In this regard, we use a 20-year time series, from 1989 to 2008, establishing a prediction of 20 years (from 2009 to 2028). This forecast is established for each one of the eight time series here considered: Montreal (Canada), Los Angeles (USA), Rio de Janeiro (Brazil), London (United Kingdom), Johannesburg (South Africa), Beijing (China), Tokyo (Japan) and Albany (Australia). Delay parameters are evaluated and results are presented in Table 3. Afterwards, simple nonlinear prediction is employed to predict

Table 3
Delay parameter analysis.

Time series	Data points	τ	D_e
Montreal (Canada)	7301	82	41
Los Angeles (USA)	7303	97	38
Rio de Janeiro (Brazil)	7083	80	25
London (United Kingdom)	7300	68	28
Johannesburg (South Africa)	7300	87	24
Beijing (China)	7303	92	61
Tokyo (Japan)	7302	41	58
Albany (Australia)	7291	81	24

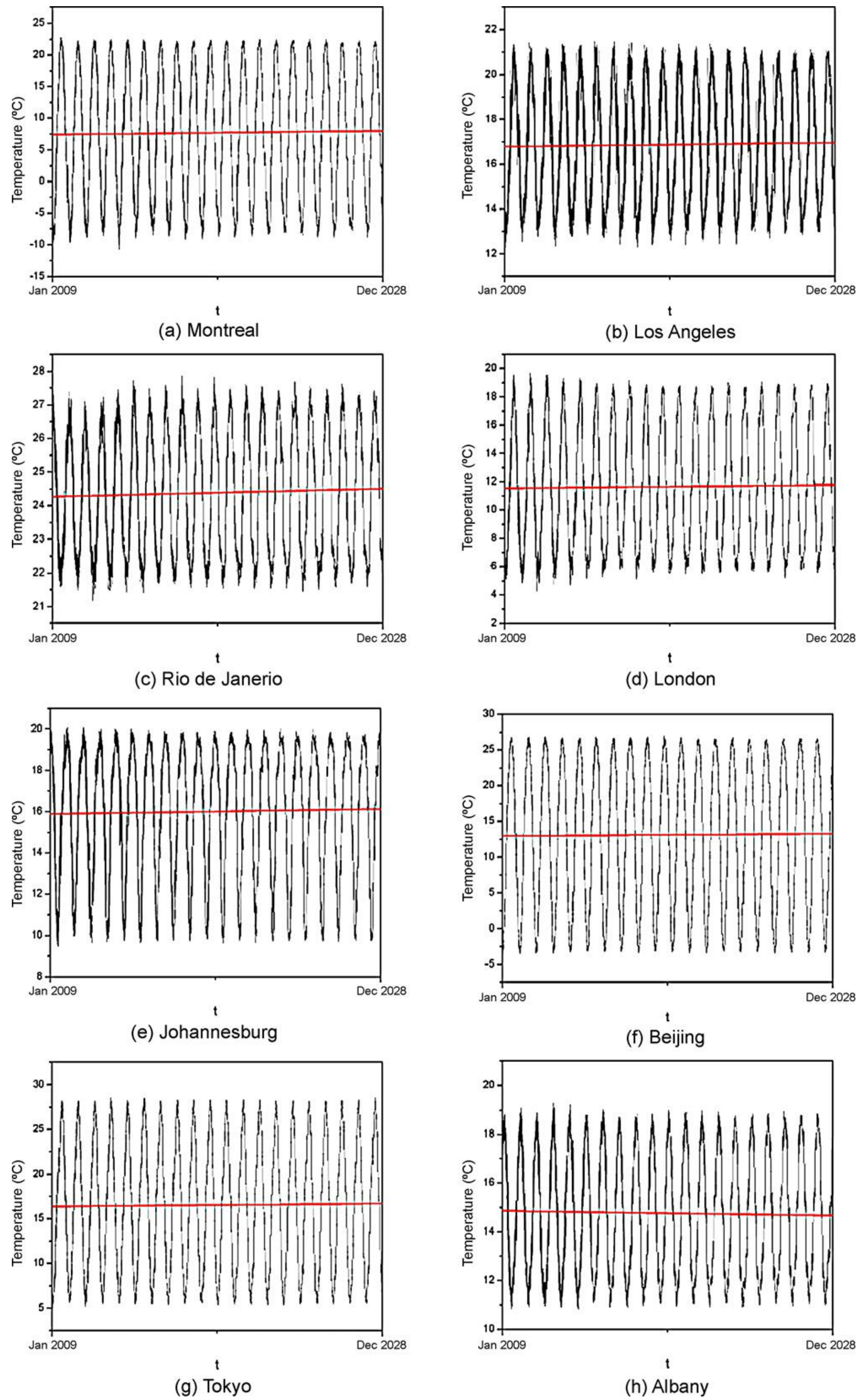

Fig. 18. Prediction from 2009 to 2028 and linear fit.

future temperature values. Temperature predictions are presented in Fig. 18. By establishing a linear match, it is possible to observe an increase in temperature for all analyzed time series, except Albany (Australia). Table 4 summarizes these results. By establishing an average value of these temperature increase it is observed an average increase of 0.29 °C. This result is coherent with Houghton (2005) that argued that the 21st century has a temperature increase in the range of 0.15–0.6 °C per decade. Concerning the average value, the forecast presents an average value of 15.15 °C related to this period.

Table 4
Prediction results and linear fit.

Time series	Prediction from 2009 to 2028	
	Linear fit (°C)	Average (°C)
Montreal (Canada)	+0.72	7.72
Los Angeles (USA)	+0.22	16.87
Rio de Janeiro (Brazil)	+0.30	24.39
London (United Kingdom)	+0.28	11.67
Johannesburg (South Africa)	+0.28	16.01
Beijing (China)	+0.39	13.16
Tokyo (Japan)	+0.38	16.57
Albany (Australia)	−0.24	14.77
Global average	+0.29	15.15

6. Conclusions

This paper deals with the analysis of the global warming dynamics from nonlinear time series. Temperature time series from Montreal (Canada), Los Angeles (USA), Rio de Janeiro (Brazil), London (UK), Johannesburg (South Africa), Beijing (China), Tokyo (Japan) and Albany (Australia) are used in order to represent the general aspects of system dynamics. Since noise contamination is unavoidable and the high dimensional characteristic of the system, the application of nonlinear tools is not a trivial task. State space reconstruction is done using the method of delay coordinates and delay parameters, time delay and embedding dimension, are respectively calculated by the method of average mutual information and the method of false nearest neighbors. Prediction is performed using the simple nonlinear prediction technique. Different number of data points and the moving average filtering are employed for model verification. Verification procedure establishes a proper number of data points and the capability of the method to represent the general behavior of time series without employ filtering. The verification analysis shows that the average value of the forecast is close to the real time series with differences that are less than 6%. Besides, more than 50% of the daily predictions present errors less than 10%. After this verification, the procedure is employed to establish prediction of future values. In this regard, 20 years forecast is performed evaluating the temperature until 2028. These results present a general increase of temperature evaluated from linear match of the predictions: 0.72 °C in Montreal (Canada), 0.22 °C in Los Angeles (USA), 0.30 °C in Rio de Janeiro (Brazil), 0.28 °C in London (United Kingdom), 0.28 °C in Johannesburg (South Africa), 0.39 °C in Beijing (China) and 0.38 °C in Tokyo (Japan). Only Albany (Australia) presents a temperature decrease of 0.24 °C. In this regard, the average temperature has an increase of 0.29 °C that represents a coherent value related to perspectives discussed in literature. The authors agree that the nonlinear tools employed in this work can be useful for the analysis of global warming.

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