Meteorological complexity in the Amazonian area of Ecuador: An approach based on dynamical system theory

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ARTICLE INFO
Article history:
Available online 25 June 2009

Keywords:
Climate
Meteorology
Chaos
Precipitation
Hydrological cycle
Ecological systems

ABSTRACT

Meteorological rhythms and trends are important components for ecosystem functioning. The complex time evolution of meteorology is often difficult to capture using linear methods. The objective of this work was to use basic concepts of dynamical system theory for assessing time evolution of daily records from six local meteorological variables collected at the Amazonian basin. We analysed rainfall, relative humidity, evaporation, minimum temperature, relative sunshine duration and evaporation/precipitation ratio. Data were collected from Puyo meteorological station, Pastaza Province, Ecuador. Data sets covered 4 years (from 1st January 2001 to 1st January 2005) (a total of 1460 data points). The TISEAN Software Package (public domain software available at http://www.mpipks-dresden.mpg.de/~tisean) was used for deriving nonlinear parameters from each time series. We found interesting evidence of chaotic behaviour as maximal Lyapunov exponents were positive for all time series considered. These results were consistent with those computed from corresponding surrogate time series. Positive Lyapunov exponents allow an estimation of the lead time of correlation for making reliable predictions.

1. Introduction

Climate has been defined as a set of atmospheric states of a dynamical, chaotic system showing deterministic variability (Lorenz, 1993). The interpretation of climate as a complex inter-variable organization is a key issue for understanding spatio/temporal evolution of ecological systems. Seminal papers have been published discussing how a novel physical theory (nonlinear dynamical system theory) can explain and/or predict the nonlinear evolution of geophysical parameters such as rainfall (Rodríguez-Iturbe et al., 1989), river flow (Wilcox et al., 1991), rainfall-runoff (Sivakumar et al., 2000), lake volume (Sangoyomi et al., 1996), sediment transport (Sivakumar, 2002), temperature (Zeng et al., 1992), sea surface pressure (Fraedrich, 1986), relative sunshine duration (Fraedrich, 1986), wind velocity (Tsonis and Elsner, 1988), pedological structures (Culling, 1988), ecological data (Turchin and Taylor, 1993) and soil formation (Phillips, 1998) among many others. Furthermore, some studies have shown that both vegetation and landscape can respond to varying climate patterns (Rinaldo et al., 1995). There are important relationships between many climate patterns and tropical or sub-tropical ecosystem functioning (e.g. coastal, marine and forest ecosystems). However, the extension of these studies to fragile tropical ecosystems is still limited due, in part, to technological constraints (e.g. meteorological data sets are still manually collected due to the lack of high performance technologies in most Third World countries). In particular the Amazon basin, as the largest natural ecosystem in the world, deserves the investigations both at local or regional spatio-temporal scales.

Recently, Sivakumar (2004) reviewed the state-of-the-art of chaos theory applications to geophysical phenomena. He recognized substantial advances from earlier identification and characterization studies to more recent prediction investigations. Yet, some minor and major problems still need to be solved before moving to this predictive field. For example, most studies do not compare their results with those derived from time series of surrogate data even when it could be a valuable procedure for accepting or rejecting a null hypothesis. That null hypothesis could be, for instance, that the time series was generated by a stationary Gaussian stochastic process. Schreiber and Schmitz (2000) have pointed out that rejecting the null hypothesis at a given significance level (e.g. $p < 0.05$) means that the nonlinear structure and its fundamental parameters (e.g. correlation dimensions, Lyapunov exponents) are still preserved in the surrogates. To our knowledge, Sivakumar et al. (1999) were the first to use the surrogate method for detecting the absence of linearity in time series of rainfall records. Another problem is that some authors work with raw data or use linear filtering for noise reduction.
While linear filters (e.g. band-pass, high-pass or low-pass filters) transform the whole data set, their nonlinear counterparts remove only those data points considered as noise. Those points are then replaced by estimates derived from a nonlinear interpolation process (Jazwinski, 1970; Harvey, 1989).

The research in nonlinear dynamics often involves deterministic forms of nonlinear differential equations. However, some recent computational projects such as TISEAN (Hegger et al., 1999) allow nonlinear dynamics analysis directly from time series of empirical data. This allows one to work directly with data of observations. The objective of this work was to use basic concepts of dynamical system theory for assessing time evolution of daily records from six local climatic variables collected at the Amazonian basin.

2. Theoretical background

There are two basic ways for chaos studies: first, solving nonlinear partial or ordinary differential equations for deriving chaotic parameters or attractors (e.g. Lyapunov exponents or fractals) (Lorenz, 1963) and second detecting chaotic dynamics directly from time series (Abarbanel, 1996; Kodba et al., 2005). In the present study we addressed four concepts commonly used within the rationale of the physics of nonlinear phenomena. They were maximal Lyapunov (or Lyapunov spectrum) exponent, fraction of false neighbors, mutual information and surrogate data. In addition, we also considered the structure of the autocorrelation function corresponding to each of climatic time series.

The Lyapunov exponent is a strong indicator of chaotic behaviour of a system. This is a parameter characterizing the separation rate of trajectories within a phase space (Sprott, 2003). Most investigations use the Lyapunov spectrum as it can be computed from the time series without an explicit mathematical model of the underlying process (Kantz and Schreiber, 2003). For chaotic systems, at least one of the Lyapunov exponents of the spectrum must be positive. In such a case a strange attractor will exist (Sprott, 2003).

Let us consider the time series data \( \{y_0, y_1, y_2, \ldots, y_n \} \), where \( y_i \) represents the observation at time \( i = 0, 1, 2, \ldots, n \). Treat these data as a trajectory and consider the Euclidean distance \( \Delta = y_n - y_{n-1} \) representing a small perturbation. The evolution of \( \Delta \) can be estimated from the time series according to the algorithm of Wolf et al. (1985):

\[
\lambda_m t = \log \frac{\sum |y_{n+t} - y_{n+t}|}{\sum |y_{n+t} - y_{n+t}|} \quad (1)
\]

where \( \varepsilon \) is the spacing within the two-dimensional construct used for defining nearest neighbors, \( t \) is time and \( \lambda_m \) is the maximum Lyapunov exponent. That is, the slope of a semi-log plot of \( S(\varepsilon, m, t) \) versus \( t \) is the estimate of the maximum Lyapunov exponent \( \lambda_m \).

Based on \( \lambda_m \) values, three cases are distinguished for physical systems:

(i) \( \lambda_m < 0 \) represents a dynamical system with asymptotic stability.

(ii) \( \lambda_m = 0 \) is characteristic of conservative dynamical systems. This could be a very rare case for open, real systems such as atmospheric systems.

(iii) \( \lambda_m > 0 \) is the exponent of unstable and chaotic systems. This case does not presume the absence of some type of self-organization and/or pattern emergence (e.g. fractal or multi-fractal structures).

The spectrum of Lyapunov exponents has been used to estimate the dimensionality of a chaotic system (e.g. fractal, information and/or correlation dimension). That dimension has been called the Kaplan–Yorke or Lyapunov dimension \( D_{KY} \) (Kaplan and Yorke, 1987).

Let us consider a \( N \)-dimensional system such that its Lyapunov spectrum contains \( \omega \) exponents. If \( \sum \lambda_i \) is the sum from \( \lambda_1 \) to \( \lambda_N \), such that \( \omega \leq N \), then there exists a maximum integer \( \mu = \mu_1 \) such that \( \sum \lambda_i \) is still positive and another integer \( \mu + 1 \) such that \( \sum \lambda_i \) is negative. The fractal dimension of the studied system would be between \( \mu \) and \( \mu + 1 \). The mathematical representation of the above theoretical rationale is (Kaplan and Yorke, 1987):

\[
D_{KY} = \omega + \frac{\sum \lambda_i}{\mu_i + 1} \quad (2)
\]

As a very simple hypothetical case, let us consider a two-dimensional chaotic system with a Lyapunov spectrum composed by two exponents, let us say \( \lambda_1 = +0.45 \) and \( \lambda_2 = -0.75 \). In such a case, the maximum integer is \( \omega = 1 \) while \( \mu_1 = +0.45 \) and \( \mu_2 = 1 \). In this case, the system would reach a Kaplan–Yorke dimension \( D_{KY} = 1.6 \).

The Lyapunov time \( (\xi) \) has been defined as:

\[
\xi = \frac{T}{\lambda_{\text{max}}} \quad (3)
\]

where \( T \) is the experimental sampling interval. The \( \xi \) parameter (often called the lead time) represents the maximal time period for making a reliable prediction. Eq. (3) has been recently used by Chaudhuri (2006) within a climatic perspective.

The false nearest neighbor is a geometrical method allowing a determination of the minimal embedding dimension \( m \) for a possible reconstruction of an attractor (Kennel et al., 1993). Its implementation permits one to find a minimal temporal separation of valid neighbors (Hegger et al., 1999). In brief, one constructs a vector sequence \( \tilde{p}(i) = \{y_i, y_{i+1}, y_{i+2}, \ldots, y_{i+(m-1)}\} \), where \( \tau \) is the embedding delay (lag) (Takens, 1981), from each point in the \( m \)-dimensional embedding space, after that a neighbor \( \tilde{p}(j) \) is found such that \( |p(i) - p(j)| < \delta \), where \( \delta \) is a small constant of the order of the standard deviation of the data. Then a normalized distance \( I_{\text{post}} \) between the \( (m + 1) \) th embedding coordinate of points \( p(i) \) and \( p(j) \) could be computed:

\[
I_{\text{post}}(i) = \frac{|\tilde{y}_{i,\text{post}} - \tilde{y}_{j,\text{post}}|}{|p(i) - p(j)|} \quad (4)
\]

If the distance of the iteration to the nearest neighbor ratio exceeds a defined threshold (standard deviation in this case), the point is considered as a false neighbor. The final result is the fraction (e.g. percentage) of false neighbors for each embedding dimension.

The concept of mutual information \( (M, \text{hereafter}) \) was introduced by Fraser and Swinney (1986) for estimating an appropriate \( \tau \) value. The mutual information between \( y_a \) and \( y_{(\text{lag}+\tau)} \) quantifies the information at state \( y_{(\text{lag}+\tau)} \) under the assumption that state \( y_a \) is known. The rationale presented by Fraser and Swinney (1986) is as follows. Given a time series \( \{y_0, y_1, y_2, \ldots, y_n \} \) with minimum \( (y_{\text{min}}) \) and maximum \( (y_{\text{max}}) \) values one computes the absolute difference \( |y_{\text{max}} - y_{\text{min}}| \), then this difference is partitioned in \( \gamma \) equally sized intervals, with \( j \) as large as a possible integer number:

\[
M_j = \frac{1}{n} \sum_{i=1}^{n} \left( P_{y_j}(\tau) \ln \frac{P_{y_j}(\tau)}{P_{y_j}(\tau)} \right) \quad (5)
\]

where \( P_{y_j}(\tau) \) are the probabilities that the variable takes a value within the \( h \)-th and \( g \)-th levels, respectively, and \( P_{y_j}(\tau) \) would be the joint probability that \( y_j \) is in the \( h \)-level and \( y_{(\text{lag}+\tau)} \) is in the \( g \)-level. The case \( P_{y_j}(\tau) = P_{y_j}(\tau) \) implies no correlation between \( y_j \) and \( y_{(\text{lag}+\tau)} \), \( (M_j(\tau) = 0) \). In general, the first minimum of \( M_j(\tau) \) versus \( \tau \) defines a suitable value for the time lag \( \tau \). This allows one the attractor reconstruction from the real time series but Fraser and Swinney
have pointed out that first minimum criterion only applies to a well marked minimum. In addition, Hegger et al. (1999) suggest modifications to this selection when the embedding dimension exceeds two. Both mutual information and false nearest neighbor methods are common tools of chaos theory for reconstructing the phase space of the attractor.

The method of surrogate data has been previously used as a nonlinearity test for physical systems (Theiler et al., 1992; Schreiber and Schmitz, 1996; Chakraborty and Roy, 2006). Surrogates are random data sets having the same autocorrelation structure as the real time series. That is, these are data sets with the same spectral properties (e.g. Fourier amplitude and phase) and the same statistical distribution as the original data (Ott et al., 1994) surrogate data construction is a Monte Carlo resampling method (Theiler et al., 1993). The basic point is to formulate a null hypothesis (e.g. the meteorological time series was generated by a Gaussian stochastic process) and then trying to reject that hypothesis by comparing results for the data set to corresponding realizations of the null hypothesis (Hegger et al., 1999). The correspondence between surrogates and the original data, in terms of relative discrepancy,

Fig. 1. Physical map showing the studied area.
either approaches to zero as the number of iteration increases or converges to a finite value acting as an uncertainty threshold.

3. Materials and methods

3.1. Geographical location and data collection

The study area is located in Pastaza Province, Ecuador, at the east of the country (Fig. 1). The meteorological station is located in Puyo City at 950 m above sea level, 01° 30’ South Latitude and 77° 57’ West Longitude. The study site is connected with two contrasting environments, the Northeast, East and Southeast sides are influenced by the Amazonian rain forest while the Northwest, West and Southwest interact with a volcanic belt. Some of these volcanoes are beside Pastaza Province (e.g. Zangay volcano ~ 75 km Southwest, Cotopaxi volcano ~ 102 km Northwest, Tungurahua volcano ~ 50 km West, Chimborazo volcano ~ 92 km West).

A total of six meteorological variables were considered in the present study: rainfall, evaporation, relative humidity, minimum temperature, relative sunshine duration and evaporation/precipitation ratio. The latter variable could be important for identifying potential changes within the hydrological cycle and surface hydrology (Assouline et al., 2008). Data sets were collected on a daily basis from 1st January 2001 to 1st January 2005 (1460 observations) using the meteorological station archives.

3.2. Nonlinear parameter estimation

Each time series was filtered using a locally projective nonlinear noise reduction filter (Ott et al., 1994) with the ghkss.exe program of the TISEAN project. This algorithm removes noise, trend and curvature effect from the data set.

The mutual.exe program (TISEAN Software) was applied for computing mutual information from each data set and to estimate an appropriate time delay (τ) within each time series. The fraction of false nearest neighbors (FNN) (Kenneletal., 1993) was also computed for estimating an optimal embedding dimension (m) for each climatic series. Lyapunov exponent spectra and Kaplan-Yorke dimensions (Kaplan and Yorke, 1987) were estimated by implementing the surrogates.exe program of the TISEAN project. This program uses the original time series as the input variable for creating a randomised sequence (e.g. another time series) with the same second order statistics as the measured data. Then it performs an iterative Fast Fourier Transform (FFT). Schreiber and Schmitz (1996) have presented detailed discussions on this method.

4. Results and discussion

4.1. Descriptive statistics

Table 1 presents the descriptive statistics corresponding to each time series. The Kolmogorov–Smirnov test of normality (p < 0.05) showed that the statistical distributions of all climatic variables except evaporation/precipitation ratio (E/P ratio hereafter) were significantly different from normal or log-normal distributions. The same nonparametric test showed that E/P ratio distribution was not significantly different from the log-normal distribution. In general, each meteorological time series exhibited a wide fluctuation range which is the first signature of climate variability (Fig. 2). The evaporation pattern showed an abrupt maximum (~11 mm) which could be an outlier due to measurement error (Fig. 2a). In particular, the studied site is one of the rainiest areas around the world with observed values over 90 mm of daily precipitation (Fig. 2b). The relative humidity remained over 77% the whole of the considered period (4 years) (Fig. 2c). We found some extremal minima within the minimum daily temperature time series (Fig. 2d). Those quasi-periodic minima might have an environmental explanation. Snow-covered volcanoes in the neighborhood of the area (all over 5000 m above sea level) contribute to the flux of cold air from West to East. Foggy and cloudy days alternate with sunny ones such that relative sunshine duration is highly variable (Fig. 2e). E/P ratio data also varied within a wide range (Fig. 2f). Approximately 35% of E/P values were >1 indicating that evaporation exceeds precipitation. We are well aware that only one meteorological station and 4 years of daily records are not sufficient for investigating a regional dynamics of climate but it permits however a meteorological investigation. In addition, that is the only source of climatic records in the neighborhood of the Amazon area of Ecuador.

In general, standard statistics (e.g. mean and/or sample variance) are only illustrative descriptors as they do not provide information about the system behaviour. Furthermore, meteorological time series might be nonstationary rather than stationary. In particular some authors (e.g. Schumer et al., 2001), working with hydrological data, have investigated distributions showing infinite variance (Levy distributions), which means that computed sample variance for a large temporal or spatial series could not converge to a constant value as is generally expected from the law of large numbers. This might be an important issue for analysing climatic time series in the future as they can be modelled using α-stable distributions (0 < α < 2). Benson et al. (2001) have pointed out that α-stable distributions differ from the normal or lognormal because the tails of the density functions drop following a power (Pareto) law. Millán et al. (2008) have illustrated this in the recent investigation based on climatic time series covering the last 31 years of monthly records.

4.2. Deterministic components of meteorological variables

The relative discrepancy between the original time series and their surrogate data counterpart is shown in Table 2. The largest number of iterations corresponded to E/P ratio sequence. This method was previously used by Sivakumar et al. (1999) for detecting presence/lack of linear components within the time series. In addition, we used it for comparing results derived from real, noise reduced series.

All the meteorological variables yielded an embedding dimension ranging between m = 5 and m = 6. Fig. 3 shows the particular case for E/P ratio after the application of the false nearest neighbor method (FNN). From a theoretical viewpoint, the minimal embedding dimension for reconstructing the E/P ratio phase space would be m = 6 as this value minimizes the fraction of points having false nearest neighbors (FNN → 0 as m → 6). For m < 6 the points are projected into neighborhoods of other points to which they do not correspond in higher dimensions. This would alter the topological structure of the phase space (Hegger et al., 1999). Thus, each studied time series represents either a five- or a six-dimensional system.
Fig. 4 represents the mutual information as a function of the time delay (time lags = 0, 1, 2, ..., 20). The mutual information dropped from a maximum value (usually associated with the maximum Shannon entropy) \( M_i \approx 0.968 \) to a minimum \( M_i \approx 0.0216 \). The global minimum value of \( M_i \) was reached at \( \tau = 16 \) time lags \( (M_i = 0.0216) \). The parameters \( m = 6 \) and \( \tau = 16 \) could be useful in recurrence analyses for locating nonstationarity and structural changes of the variable as discussed by Eckmann et al. (1987). Note that \( \tau = 16 \) implies, approximately, ACF = 0 as shown in Fig. 5. The ACF exhibited approximately the same exponential decrease with time lag for all the studied variables. According to Wilks (1995), an exponential drop of autocorrelation as a function of time lag is consistent with a first order Markov process representing an underlying chaotic structure.

Positive Lyapunov exponents were found for all meteorological time series (noise reduced data) as shown in Table 3. Similar results were also derived from corresponding time series of surrogate data. The most predictable variable was the minimum temperature (lead time of 6.45 days) while the less predictable was

<table>
<thead>
<tr>
<th>Climatic variable</th>
<th>No. iterations</th>
<th>Relative discrepancy</th>
</tr>
</thead>
<tbody>
<tr>
<td>Evaporation (mm)</td>
<td>67</td>
<td>0.0093</td>
</tr>
<tr>
<td>Precipitation (mm)</td>
<td>108</td>
<td>0.405</td>
</tr>
<tr>
<td>Relative humidity (%)</td>
<td>64</td>
<td>0.030</td>
</tr>
<tr>
<td>Minimum temp. (°C)</td>
<td>17</td>
<td>0.039</td>
</tr>
<tr>
<td>Sunshine duration (h)</td>
<td>80</td>
<td>0.019</td>
</tr>
<tr>
<td>E/P ratio</td>
<td>321</td>
<td>0.072</td>
</tr>
</tbody>
</table>

Fig. 2. Noise reduced time series.
the precipitation (lead time of 1.38 days). These results should be interpreted with caution as the Kaplan–Yorke ($D_{KY}$) dimension tends to increase as lead time decreases ($\xi^{-1/m}$). Both precipitation and $E/P$ ratio rendered the largest $D_{KY}$ values of 2 (Table 3) indicating a high complexity of the pattern as $P_{lv}/C_{25}$ in Eq. (2).

$D_{KY}$ values are usually interpreted as the information dimension estimates. We treat the information dimension as a measure of confidence. For example, as time scale for prediction is reduced ($\xi$ value diminishes), the confidence on the prediction increases. This interpretation tries to separate information and entropy concepts. On the other hand, many authors could argue that larger information dimensions indicate the need of much more information for a precise prediction of system evolution. However, in many cases weather prediction from 1 day to the next requires less detailed information than that necessary for larger time scales as any variation of initial conditions could be irrelevant a shorter time scales. Lovejoy et al. (2007) and Maxwell et al. (2007) have discussed the relevance of atmospheric turbulence and boundary layer variation for long-term weather prediction.

Most published studies on deterministic forms derived from climatic data are based on precipitation, temperature and, in some cases, relative sunshine duration. However, there exists a strong interaction between all climate components. Precipitation and evaporation are two main driving forces of water cycle. Precipitation regimes depend on evaporation patterns and the combination of both variables ($E/P$ ratio in this case) is a key point for understanding the hydrological cycle. Under balanced (stable) climate conditions it is usually expected that precipitation exceeds evaporation ($E/P < 1$). However, the rapid increase of $E/P$ ratio has been detected in this area (Millán et al., 2008). In particular, $\lambda_m > 0$ values for $E/P$ ratio could be signals of an unstable hydrological cycle showing short time scales for useful predictions. In this way, one could expect a nonlinear response of ecosystem forced by climate/water cycle instability. This can include alterations of geomorphic patterns (Phillips, 2006), vegetation cover and/or biodiversity redistribution. Some national sources report on a rapid increase in deforestation and land use change between 1970 and 1990 in this area (FAO, 2005).

Fig. 6 illustrates the phase space reconstruction corresponding to $E/P$ ratio. It represents a three-dimensional projection using an optimal time delay $\tau = 16$. At a first sight it shows a very complicated dynamics as compared to those attractors derived from the solution of deterministic differential equations such as Lorenz attractor (Pasini et al., 1998) or the generalized Volterra–Lotka system (Blasius et al., 1999). Both two- and three-dimensional representations are only illustrative since the minimal embedding dimension was $m = 6$ as can be seen from Fig. 3. Many investigations have shown that natural systems usually embed high-dimensional rather than low-dimensional structures in terms of correlation dimension (Fraedrich, 1986; Wang, 1995).

<table>
<thead>
<tr>
<th>Climatic variable</th>
<th>Data source</th>
<th>$\lambda_m$</th>
<th>$D_{KY}$</th>
<th>$\xi$ (days)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Evaporation</td>
<td>Noise reduced</td>
<td>0.351</td>
<td>1.644</td>
<td>2.85</td>
</tr>
<tr>
<td></td>
<td>Surrogates</td>
<td>0.183</td>
<td>1.331</td>
<td>5.46</td>
</tr>
<tr>
<td>Precipitation</td>
<td>Noise reduced</td>
<td>0.719</td>
<td>2.000</td>
<td>1.39</td>
</tr>
<tr>
<td></td>
<td>Surrogates</td>
<td>0.718</td>
<td>2.000</td>
<td>1.39</td>
</tr>
<tr>
<td>Relative humidity</td>
<td>Noise reduced</td>
<td>0.246</td>
<td>1.470</td>
<td>4.06</td>
</tr>
<tr>
<td></td>
<td>Surrogates</td>
<td>0.121</td>
<td>1.214</td>
<td>8.26</td>
</tr>
<tr>
<td>Minimum temperature</td>
<td>Noise reduced</td>
<td>0.155</td>
<td>1.213</td>
<td>6.45</td>
</tr>
<tr>
<td></td>
<td>Surrogates</td>
<td>0.182</td>
<td>1.273</td>
<td>5.49</td>
</tr>
<tr>
<td>Sunshine duration</td>
<td>Noise reduced</td>
<td>0.412</td>
<td>1.824</td>
<td>2.43</td>
</tr>
<tr>
<td></td>
<td>Surrogates</td>
<td>0.236</td>
<td>1.335</td>
<td>4.24</td>
</tr>
<tr>
<td>$E/P$ ratio</td>
<td>Noise reduced</td>
<td>0.605</td>
<td>2.000</td>
<td>1.65</td>
</tr>
<tr>
<td></td>
<td>Surrogates</td>
<td>0.641</td>
<td>2.000</td>
<td>1.56</td>
</tr>
</tbody>
</table>
4.3. Deterministic component and time scale

The deterministic component of a nonlinear dynamical system can appear or vanish as a function of time scale. Although these systems can present both deterministic and stochastic components, chaos is usually interpreted as an emergent pattern. In the particular case of the present study, different time scales rendered different Lyapunov exponents including negative exponents which are typical of no chaotic behaviour. Table 4 shows the results derived from 2 years of daily records after filtering each time series (730 data points) (1st January 2001 to 1st January 2003) where smaller $\lambda_m$ values were computed as compared to those derived from 4 years of daily records ($N = 1460$). Therefore, the temporal resolution is an important issue for separating deterministic components from time series resembling random structures.

5. Conclusions

We have used some basic concepts of chaos theory and nonlinear time series analysis for characterizing six meteorological variables collected near to the Amazonian rainforest. All of them had positive Lyapunov exponents separating deterministic and stochastic components which could be useful for making reliable predictions using an appropriate time scale resolution. The use of time series of surrogate data is also valuable for addressing data limitations and providing a confidence on results.

Acknowledgements

We are grateful to Dr. A. Tsonis (University of Wisconsin) for his constructive comments on the initial results of this work. The first author thanks the National Institute of Meteorology and Hydraulic Resources (Ecuador) for permitting the access to meteorological data. We also appreciate the valuable material and financial support from Amazonian State University, Ecuador.

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