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Citation: Chaos **25**, 123123 (2015); doi: 10.1063/1.4938188 View online: http://dx.doi.org/10.1063/1.4938188 View Table of Contents: http://scitation.aip.org/content/aip/journal/chaos/25/12?ver=pdfcov Published by the AIP Publishing

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Reconstructing the micrometeorological dynamics of the southern Amazonian transitional forest

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(Received 23 July 2015; accepted 8 December 2015; published online 29 December 2015)

In this work, we reconstruct and analyze the micrometeorological dynamics of the transitional forest located south of the Amazon basin. For this, we use time series of micrometeorological variables collected over five years in the transitional forest of Mato Grosso (Brazil). We employ local feature analysis, a recently proposed extension of principal component analysis, to extract the most relevant physical variables from this set. We show in this way that temperature records contain most of the dynamical information in all seasons. Based on this result, the dimensionality of the space spanned by the system's dynamics and the properties of the so defined attractors are obtained. In the dry season, the system presents a robust oscillatory character described by a well-defined limit cycle. In the wet season, the dynamics becomes more irregular but can still be seen as a periodic behavior affected by external noise. These results can help to develop accurate models for the meteorology of the Amazonian transitional forest and can thus lead to a better understanding of this important ecosystem. © 2015 AIP Publishing LLC. [http://dx.doi.org/10.1063/1.4938188]

The transitional forest located in Mato Grosso (Brazil) connects the Amazon Forest, the "lungs of the Earth," to the Brazilian Savannah. It plays a pivotal role in the exchange of heat and mass between the rainforest and its surroundings. Understanding its dynamics is thus essential to predict the evolution of the Amazon Forest and, in particular, the potential effects of deforestation. In this work, we analyze the micrometeorology of this system and show that most of the variability of the local meteorology can be captured simply by following the time evolution of the air temperature. We also show with nonlinear time series analyses that the micrometeorological dynamics corresponds to a noisy limit cycle that can be embedded in a three-dimensional phase space. Such information is important for the future development of efficient models for this crucial region.

I. INTRODUCTION

Assessing the dynamics of the atmosphere–biosphere interaction in natural ecosystems is unarguably a very complex problem. These systems involve a great variety of physico-chemical and biological phenomena.^{1,2} It is thus expected that an appropriate description of their behavior incorporates many interacting variables, such as the temperature of the atmosphere, the type and density of vegetation, and the level of humidity, to cite but a few.^{3–5} These systems are moreover open to (possibly fluctuating) energy and matter fluxes maintaining

them far from equilibrium. Despite these inherent difficulties, the present-day attention paid to global climate change has led to numerous scientific efforts aimed at analyzing and understanding the dynamics of such ecosystems.⁶

The most traditional way to analyze complex dynamics is based on the derivation and analysis of evolution laws for a selected set of variables, which are considered to be representative of the system's state. Because of the aforesaid level of complexity, this approach can capture only a fraction of the real-world intricate dynamics. In order to reduce the complexity of a model, one could be tempted to overlook phenomena and/or variables that are actually important, leading to inaccurate interpretations or predictions. Alternative approaches are thus highly desirable in order to fully characterize the dynamical properties of the class of systems under consideration.

In this context, new analysis techniques were developed in the 1990s, which rely directly and exclusively on experimental time series.⁷ They are based on a reconstruction of the system's dynamics in the space spanned by its constitutive variables (the phase space). In such space, the time series define geometrical objects (known as manifolds), the properties of which can be used to extract important information on the system. One can, for example, deduce the number of variables that are needed to model the observed phenomena, or quantify the degree of complexity of the dynamics.⁸ In this work, we use such nonlinear time series analyses to investigate the micrometeorological dynamics of an ecotonal transitional forest located south of the Amazon basin.

The Amazon rainforest is known to regulate not only the local but also the global climate: understanding what controls its dynamics is thus of crucial importance. The transitional forest we are studying here connects the Amazon

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Forest to the Brazilian Savannah. It plays an important role in the exchange of heat and mass between the rainforest and its surroundings. Furthermore, the region is marked by an intensive anthropogenic influence, since it is located in the socalled "arc of deforestation," where changes in land use are particularly intense.

A detailed knowledge of the dynamical features of the transitional forest is thus mandatory for understanding the meteorology of this important region, as well as for predicting the potential effects of deforestation. As of today, the micrometeorology and the dynamics of the surface-atmosphere exchanges of water and energy in such forests are however only poorly understood.9 We employ in this context time series analysis techniques and study the dynamical properties of various physicochemical variables collected during more than 5 years in Mato Grosso. We extract, from these measurements, the variables that contribute the most to the observed meteorological variability. We moreover reconstruct the underlying meteorological attractor, which corresponds to a well-defined and robust class of dynamics. These results can lead to a substantial improvement of the level of knowledge of this system, in particular, in terms of modelling and sensitivity analysis.

In Sec. II, we first detail the methods used to measure the meteorological variables of interest. Section III is devoted to a description of the local ecosystem and a presentation of the most salient features of the time series. In Section IV, we describe and use Local Feature Analysis (LFA), which is an extension of principal component analysis (PCA), in order to extract the most relevant measurements from the whole database. Section V details the reconstruction of the phase space trajectories based on the selected variable (namely, temperature). A special emphasis is put on the changes of the properties of the attractor between the dry and wet seasons. In Section VI, we assess how such information is important for the modelling and understanding of the micrometeorology of such ecosystems. We point, in particular, to potential future studies that could build on the acquired knowledge.

II. METHODS

The micrometeorological variables we present below were obtained through a set of equipment mounted on top of a 42 m tower, located 50 km NE of Sinop, Mato Grosso, Brazil (11° 24′ 75″ S, 55° 19′ 50″ W), 423 m above sea level. The equipment consists of a three-dimensional sonic anemometer (CSAT-3, Campbell Scientific, Inc., Logan, UT, USA) that measures the three orthogonal components of wind velocity; a psychrometer (HMP45C, Campbell Scientific, Inc.) with a digital converter measuring both temperature and humidity; a pyranometer (LI-200SA Sensor, LI-COR, Inc., Lincoln, NE, USA), which measures the solar radiation over the canopy; a quantum sensor (LI-190SZ, LI-COR, Inc.), to obtain the photosynthetically active radiation; and an open-path infrared gas analyzer (LI-7500, LI-COR, Inc.), used to measure the concentration of CO₂ and H₂O vapor. The net solar radiation was also measured using a ventilated radiometer (NR-LITE, Kipp&Zonen, Bohemia, NY, USA). The equipment was calibrated every month. Note that the recalibration procedures did not induce substantial breaks in the time series.

The data collection was carried out by a data logger (CR 10X, Campbell Scientific, Inc., Ogden, Utah) and a laptop, both powered by batteries fueled by solar energy. The raw data were collected at a frequency of 10 Hz. The temperature, water vapor, and carbon dioxide concentrations correspond to 30 min means. Note that the time series taken at Sinop sometimes show interruptions that can be due to lightning, rain, battery failure, animal action, etc. We thus selected, for the analyses, the longest available uninterrupted periods for each representative season (see the description of the local ecosystem). These data sets extend from one month up to two months.

III. DESCRIPTION OF THE LOCAL ECOSYSTEM

The region where the measurements were made corresponds to the transitional forest located between the Amazonian Forest and Brazilian Savannah (Cerrado). This forest is semi-deciduous, i.e., the leaves fall only partially during the year. The soil has a sandy texture, is poor in nutrients, and is highly porous so that water is drained rapidly (within 4-7 days⁹). The vegetation typically consists of 25-28 m tall Amazonian evergreen trees, with a mean trunk diameter of 10 cm. This vegetation comprises approximately 80 different species and 35 families. However, Priante Filho et al.¹⁰ showed that about 50% of the trees are either Tovomita cf. schomburgkii, Protiumsagotianum, Brosimumlactescens, or Dialiumguianense. The local climate has been characterized as being of the Am-equatorial monsoon type, following the Köppen-Geiger classification.¹¹ The air is hot and humid, with a mean annual temperature of 24 °C.

We here focus on two seasons: the wet season, which extends from December to February, and the dry season that takes place from June to August. The characteristics of the ecosystem change significantly from one season to the other. The so-called dry season is characterized by relatively frequent long rainless periods (several days), with a mean rainfall of 8 mm/month (see Ref. 12). A fraction of the leaves fall during this season due to hydric stress reducing the leaf area index from 5 m² m⁻² to 4 m² m⁻². This leads to an average reduction of 20% in the canopy density. During the wet season, rain is much more frequent (and sometimes heavy). In this season the mean rainfall is approximately 350 mm/month.¹²

IV. CHOOSING THE MOST RELEVANT VARIABLES

The different physical variables measured in Sinop represent a huge amount of data. Our objective here is not to analyze in detail the behavior of each of these variables as a function of time, but rather to identify the class of dynamical systems to which the meteorology of this transitional forest belongs. We need to this end to extract the most salient features from the whole set of measurements. Moreover, we want to be able to relate such a reduced description to physically meaningful quantities.

In this section we use an extension of PCA in order to do so. In classical PCA, one considers an ensemble $X \in \mathbb{R}^{M \times N}$, consisting of a set of *M* different centered and normalized measurements (vectors $x \in \mathbb{R}^M$), each containing *N* data points. This set of vectors is used to construct an $M \times M$ covariance matrix

$$C = \frac{1}{N-1}XX^T.$$
 (1)

Such a matrix admits eigenvalues of decreasing order: $\omega_1 \ge \omega_2 \ge \dots \omega_M$. The corresponding eigenvectors Ψ_i are called the principal components. Consider now the matrix $P \in \mathbb{R}^{M \times r}$ whose columns are the *r* first principal components. This matrix can be used to obtain a lower-dimensional representation $Y \in \mathbb{R}^{r \times N}$ of the original data, consisting of vectors $y \in \mathbb{R}^r$, through a projection on the selected principal components

$$Y = P^T X. (2)$$

However, these features are "global," since they are linear combinations of the originally measured variables, and cannot be easily related to physically meaningful quantities.

LFA is a recently introduced extension of PCA, whose objective is to extract the most relevant physical features from the original data set. It was originally designed for image analysis by Penev and Atick,¹³ and later extended to the analysis of time series coming from physicochemical processes (see, for example, Ref. 14). The basic idea consists in identifying which of the physical modes contribute the most to the principal components. Indeed, each row $\Psi_{r,i}$ of these components corresponds to one of the *M* original measurements. The first step in LFA is to define a pool of candidate features, S_{σ} , based on the values taken by the rows P_i of *P*

$$S_{\sigma} = \left\{ i : \frac{\|P_i\|_2}{\max_i \|P_i\|_2} > \sigma \right\},\tag{3}$$

where σ represents a lower bound. This operation selects the physical measurements that contribute the most to the norm of the different principal components (σ being a tuning parameter). The first local feature is the one that contributes the most to the variability of the components, i.e., it is the feature with coordinate

$$\underset{i}{\operatorname{argmax}} \left(\frac{P_i \Lambda P_i^T}{\|P_i\|_2^2} \right), \tag{4}$$

in which Λ is a diagonal matrix containing the *r* first eigenvalues. The subsequent feature is chosen as that which is the least correlated to the first physical mode. We refer again the reader to Xue *et al.*¹⁴ for further details.

We performed PCA on the original database, which consisted of 8 different measurements: The air temperature (°C), the total incoming solar radiation (W·m⁻²), the net radiation (W·m⁻²), the photosynthetically active radiation (μ mol·m⁻²·s⁻¹), the CO₂ concentration (mg·m⁻³), the H₂O concentration (mg·m⁻³), the wind velocity (m·s⁻¹), and the wind direction (°). We found that 5 principal components are in each case enough to capture most of the variability of the signal (more than 95% of the cumulative normalized energy). A representative example of the contribution of the modes to the total variability is given, for each season, in Table I. We note that the 90% threshold is crossed in each case for a critical number of 3 modes. This suggests that the dynamics of the system at hand can be embedded in a three-dimensional space spanned by the corresponding principal components. This point will be discussed further in Sec. V.

We also applied LFA, using the aforementioned procedure. The first 5 principal components were kept, and a value of $\sigma = 0.8$ was used to select a pool of candidates from the measured physical variables. This value was chosen so as to extract at least 5 dominant physical modes from the principal components for all the time series we had at our disposal. The top 3 dominant measurements are the same for the dry and the wet seasons: The air temperature, the CO₂ concentration, and the water vapor concentration.

This result is interesting in the sense that it allows one to list the physical variables that seem to be important for the considered local meteorology, at least in terms of variability of the observations. Remember that our objective here is not to build a model based on such variables, but rather to define the class of the dynamical system at hand. For this, it is sufficient to identify a single variable carrying enough information to characterize the system in the different seasons. Interestingly, not only is the pool of the most powerful local features identical in the dry and the wet seasons, but the air temperature is also in each case the first local feature, as given by the criterion (4). Moreover, it is seen to contribute by itself to more than 80% of the norm of the first principal component. To some extent, one could say that temperature is the variable that best "records" the variability of the local meteorology. It is interesting to note that this result represents, in some way, a data-based confirmation that temperature is the most relevant quantity to be studied when understanding or modelling a local meteorology.

We will thus use this variable in the remainder of this work to quantify the dynamical dimensionality, and reconstruct, from there, trajectories in phase space. An example of the time evolution of air temperature is given in Figure 1, for the sake of illustration. As is well known, temperature presents a clearly cyclic character in both seasons, with the wet season being more irregular than the dry one.

TABLE I. Eigenvalue number and total energy of the first principal components for, respectively, the micrometeorological data of June 2002 (1032 uninterrupted measurements) and February 2001 (890 interrupted measurements).

Mode number	Cumulative normalized energy (June 2002)	Cumulative normalized energy (February 2001)
1	72.0	64.1
2	83.0	81.4
3	90.9	91.7
4	94.3	96.2
5	97.6	98.4
6	99.6	99.9

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V. PHASE SPACE AND DIMENSIONALITY OF THE ATTRACTOR

The phase space dimensionality is an important property that helps to select models with appropriate dimensionality and complexity. The possibility to retrace the phase space trajectories is important to assess the nature of the dynamical attractor involved (limit cycle, strange attractor, etc.) and compare it with the attractor generated by models.

In order to determine these quantities, we employed the time-delay embedding technique. In such an approach, one creates lagged time series from the original one (here, the temperature) by introducing a time delay τ , as discussed amongst others in Ref. 7. As shown by Takens¹⁵ and Sauer,^{16,17} this reconstruction preserves many of the properties of the unknown original dynamical system. For example, if the unknown dynamics has an attractor A with box counting dimension d_A , this attractor can be embedded in a d_E dimensional reconstructed phase space, where the embedding dimension $d_E \ge 2 d_A + 1$. It should also be noted that, although the reconstruction does not preserve the geometric shape of the original phase space structures, the figures resulting from plotting the time lagged series as a function of each other are similar to the ones that would be obtained by plotting the most relevant variables of the original dynamics.^{7,18} Other important properties such as the Lyapunov exponents of trajectories in phase space are conserved as



FIG. 1. Temperature for the first ten days of (a) June 2002 (dry season) and (b) February 2001 (wet season).

well. In this way, the analysis of the lagged time series can offer important information on the system dynamics, even if the original time series corresponds to a single variable.

We will here focus on two dynamical invariants that could be important for future modelling: the minimal number of independent dynamical variables d_M needed to describe the system's dynamics, and the dimension of the underlying attractor d_A . The aforementioned embedding dimension d_E represents a sufficient condition under which the attractor can be reconstructed unambiguously, but very often the necessary number of dynamical variables will be less than d_E . There are many ways of estimating this minimal embedding dimension d_M . We used the saturation of correlation integrals and confirmed the dimension obtained in this way with the False Nearest Neighbors method, as explained later. The dimension of the attractor can also be estimated in several ways. We here choose to focus on the correlation dimension D_2 , but other choices of generalized dimensions are possible (see Ref. 19 for a definition and a discussion of the dimension spectrum D_q). Note that from a numerical point of view, the values taken by the most common choices $(D_0, D_1, and$ D_2) are typically very close to each other.

A. Choosing the time delay

A first step towards the identification of the aforementioned dimensions consists in choosing an appropriate time delay τ for the construction of the set of delayed time series. A good choice for τ is the time for which the intervaldependent average mutual information of the time series undergoes a minimum. Fraser and Swinney²⁰ suggested that this choice is appropriate in the sense that the delayed time series defined in this way are as independent from each other as they can be, and hence that they contribute to the information contained in the signal whilst minimizing redundancy. We computed the average mutual information, using the TISEAN 3.0.1 package²¹ for different seasons and years. The minimum time was always seen to be comprised between 4.5 h and 5.5 h, which is in line with previous results.²² For the sake of simplicity and comparison between time series, we thus decided to choose $\tau = 5 h$ for all data treatments.

B. Embedding and attractor dimensions

If the original attractor has been reconstructed correctly from the time series, the phase space properties depending on the distance between points should be independent of the particular choice of $d_E \ge d_M$. This is the case for the correlation integral

$$C(r) = \frac{1}{L(L-1)} \sum_{\substack{i,j=1\\i \neq j}}^{N} \theta\Big(r - |\vec{Z}_i - \vec{Z}_j|\Big),$$
(5)

which measures the average number of pairs of data points in the reconstructed phase space whose distance does not exceed r. In this equation, $\theta(u)$ is the Heaviside function



FIG. 2. Estimated correlation dimension D_2 as a function of the embedding dimension d_E for temperatures collected in: (a) February, 2001. (b) June and July, 2002. (c) February, 2003. (d) July, 2005. (e) January and February, 2006. (f) August, 2006.

$$\theta(u) = \begin{cases} 0, & u \le 0\\ 1, & u > 0 \end{cases}$$

and \vec{Z}_i is a vector in the reconstructed phase space corresponding to the set of values of the variable (temperature) at times t_i , $t_i + \tau$, ..., $t_i + (d_E - 1)\tau$, i.e.,

$$\vec{Z}_i = \{T(t_i), T(t_i + \tau), T(t_i + 2\tau), ..., T(t_i + (d_E - 1)\tau)\}.$$
(6)

The correlation integral is calculated for increasing values of d_E , until the slope of the $\log(C)/\log(r)$ curve becomes independent of d_E , which gives an estimate for d_M .

The dimension of the attractor can also be estimated in this way. Indeed, $C(\mathbf{r})$ is expected to be proportional to r^{D_2} ,⁸ so that the slope of the log(C) vs log(r) curve itself is an estimate for D_2 . The procedure consists in estimating the aforesaid slope for different values of d_E . It is typically observed that D_2 increases with d_E , until it reaches a plateau for a large

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enough embedding dimension. Both the minimal phase space dimension and the attractor dimension can thus be estimated by identifying the values of d_E and d_A for which the D_2 vs d_E curve reaches a constant value. The results, obtained with the traditional Grassberger–Procaccia algorithm first described in Ref. 23, are depicted in Figure 1. These results were almost identical to those obtained with more advanced algorithms, such as the one proposed by Takens²⁴ or Theiler.²⁵

In most cases, the graphs exhibit a plateau indicating that the underlying dynamical system can be characterized by a finite-dimensional attractor in a finite-dimensional phase space. There are however differences between the dry and the wet seasons. In the dry season (Figures 2(b), 2(d), and 2(f)), a distinct plateau is reached for which $D_2 \approx 1.5$ and $d_M \approx 5-6$. It thus appears that this season can be characterized by a relatively low-dimensional attractor embedded in a 5-6 dimensional phase space. In fact, a two-dimensional phase space could even be sufficient to enclose such an attractor, since its dimension is lower than 2.

In the wet season (Figures 2(a), 2(c), and 2(e)), the plateau is less pronounced and is reached at $D_2 \approx 2$. On one hand, the value we obtain for D_2 suggests that a three-dimensional space could be used, since it is enough to embed a two-dimensional attractor. On the other hand, the plateau is reached in the analyses for much larger values, $d_E \ge 8$. It is important to point out here that these values exceed Ruelle's criterion²⁶ following which one should not exceed a value of $d_E \approx 6$. Consequently, we cannot draw any firm conclusion about the embedding dimension based only on the present technique. Because of this, and since the convergence to a plateau is not always obvious in the wet season, we additionally performed a False Nearest Neighbors analysis as initially proposed by Kennel et al.²⁷ to confirm the best value of the embedding dimension. These calculations, performed with the TISEAN package for time series analyses, lead to $d_M = 2$ or 3, depending on the time series. This result suggests a conservative choice of $d_M = 3$, i.e., the dynamics of the wet season needs to be embedded in a higher dimensional space than that of the dry season.

The lower dimensionality of the dynamical attractor observed during the dry season is a robust trend. The attractor's correlation dimension is seen to "oscillate," for all years, between a value of approximately 2 for the wet season and 1.5 for the dry one. As said before, this difference is indicative of the fact that the temperature pattern is more complex during the wet season. This difference is somewhat apparent in the original time series (Figure 1), but this analysis confirms that there is a reproducible qualitative difference between the seasons. This observation is interesting not only in the context of the characterization of the local climate but also for the future development of model-based forecasts.

The attractors for the wet and dry seasons can be constructed from the temperature time series by simply plotting the delayed data as functions of each other. For example, Figure 3 plots three-dimensional projections of the attractors, respectively, for July 2002 and February 2003. At first sight, the two attractors look very similar in the sense that they both define a cyclic shape. The main difference between the two is that the data seem to be more concentrated along the cycle in the dry season as compared with the wet one.



FIG. 3. Reconstructed attractors from the temperature time series of July 2002 (left) and February 2003 (right). An optimal time delay of 5 h has been used.

This observation raises the important question of defining the class of dynamical behaviors to which the observed meteorology belongs. Indeed, the different seasons are characterized by low-dimensional attractors whose dimension seems to exceed 1. Such values suggest that the attractor could be a torus or a strange (fractal) object. However, the phase space reconstruction indicates that well-defined, single-looped cycles are produced, at least for the case of the dry season. The time series moreover present a clear periodic character. As periodic behaviors correspond to limit cycles, one could have expected to find one-dimensional objects in phase space.

The fact that we find higher dimensional attractors can be explained in mostly two ways. First, one could be confronted to a signal that actually is chaotic, quasi-periodic, or multi-periodic but the resolution of the trajectories in phase space would not be enough to see such behaviors. The other possibility is that noise is superimposed on a periodic signal:



FIG. 4. Fourier power spectra, obtained from the autocorrelation function of the temperature time series of (a) June 2002 and (b) February 2003.

It is known that random perturbations tend to increase artificially the dimension of the attractors extracted from time series (see, for example, Ref. 28). We thus computed the Fourier power spectra of the signals in order to discriminate between these two possibilities (see Figure 4, for two examples). Both the dry and the wet seasons are characterized by a well-defined, single periodic mode (together with the harmonic due to finite time series).

To make sure that what we observe is indeed oscillations and not narrow-banded chaos, we additionally performed a few recurrence analyses. We extracted next-maximum maps and next-period maps from our time series, which are qualitatively equivalent to Poincaré sections of the attractor. They both show (not displayed here) that the dynamics is characterized by a collection of points close to the diagonal, and that most of the points are centered on the main amplitude (or period, respectively). A chaotic time series would have generated continuous lines or collections of aligned dots extending far away from the diagonal line. We thus conclude from these different analyses that the micrometeorological dynamics correspond to noisy periodic behaviors: both seasons present a robust underlying limit cycle, but the perturbations are substantially stronger in the wet season.

VI. CONCLUSIONS AND OUTLOOK

Using nonlinear time series analyses, we have shown that the micrometeorological dynamics of the Amazonian transitional forest can be qualitatively assessed on the basis of temperature measurements only. Thanks to phase space reconstruction techniques, we have also determined that the observed dynamics can be seen as a periodic behavior perturbed by fluctuations both in the wet and dry seasons, despite the apparently chaotic character of the time series recorded in the wet season.

An interesting observation is that the dynamics of the system is almost perfectly stationary (in the weak sense). The correlation dimension, time lag, and shape of the attractor were indeed practically indistinguishable from one year to the other. Moreover, the attractor also seems to remain qualitatively the same for the dry and wet seasons. It is only during the transition seasons that drifts and non-stationarity could be observed (not reported in this work). This is reflected also in the Fourier analyses, which present no sign of non-stationarity during a given season: the spatiotemporal Fourier maps show almost no drift in the main frequencies. This feature is in fact quite unexpected. Indeed, the intense local deforestation and other changes in land use could be expected to produce visible trends in at least some of the measured data. The local meteorology is thus unexpectedly robust, and the reasons behind such robustness should be investigated in the future.

How can such information be used for building efficient models for this ecosystem? One important piece of information is that the low dimensionality of the attractors suggests that a relatively low-dimensional model could be constructed for this system. The analysis of the correlation dimension, together with principal component and False Nearest Neighbours analyses point to the idea that already a 3-variable description could correctly model the dynamics of both seasons. Although noise is known to affect the results of time series analyses, our results strongly suggest that a low-dimensional dynamical modeling of the region of interest is feasible. An important aspect that any further modelling should be able to reproduce is that although the two seasons define a limit cycle with well-defined periodicity, the dynamics of the wet season is subject to important noise. This suggests that a stochastic approach would be mandatory. Since we observe that the correlation dimension and the width of the peaks in the Fourier power spectra slightly increase when fluctuations are stronger, this stochastic model should be such that the processes inducing the fluctuations (like rain, cloud cover, etc.) act as disorganizing variables.

The fact that there exists a low dimensional representation of the micrometeorology forms, by itself, an interesting conclusion for future modelling efforts. But the results presented here can also help in choosing the "best" physicochemical variables to include in such a model. The oscillatory character of the temperature profiles can be mostly attributed to the periodic income of energy related to the day/night cycles. Virtually all the existing models for energy balance show that the rate of change of temperature is proportional to the incoming solar radiation (see for example, Ref. 29). A first natural choice for physical quantities to include in modelling would thus be the solar radiation. Moreover, we showed, thanks to local feature analysis, that among all the measured micrometeorological variables, the three most "powerful" physical modes are the air temperature, the CO₂ concentration, and the water vapor concentration. These quantities

represent the best candidates to be put into a threedimensional model together with the incoming solar radiation.

Finally, an important problem that needs to be addressed is the origin of the noise that perturbs the oscillations. A central question that should be answered is whether the noise is additive or system specific. The fact that fluctuations are more intense in the wet season suggests that the disturbing agents could be found in clouds, rain, and vegetation. Clouds reduce the incoming solar radiation by blocking sunlight, which would affect the heating of the atmosphere after sunrise. Rains tend to cool down the atmosphere and to affect its heat capacity because of changes in the humidity levels. Atmospheric turbulence is thus expected to be a key component of the perturbations we observed. The role played by the changes in the vegetation, from one season to the other, should also be important. We thus expect noise to be system specific, and consequently season-dependent. A delicate problem is to understand how all these phenomena can be introduced as noise or time-dependent parameters in a model for the local meteorology of the transitional forest we are studying here. This question will be addressed in a subsequent work, which is focused on the development of such a model.³⁰

ACKNOWLEDGMENTS

The authors would like to express their gratitude to Coordenação de Aperfeiçoamento de Pessoal de Nível Superior (CAPES), for financial support. We also thank Ceri Middleton for fruitful discussions and proofreading of the manuscript.

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