Abstract. The possible chaotic nature of the turbulence of the atmospheric boundary layer in and above a deciduous forest is investigated. In particular, this work considers high resolution temperature and three-dimensional wind speed measurements, gathered at six alternative elevations at Camp Borden, Ontario, Canada (Shaw et al., 1988). The goal is to determine whether these time series may be described (individually) by sets of deterministic nonlinear differential equations, such that: (i) the data’s intrinsic (and seemingly random) irregularities are captured by suitable low-dimensional fractal sets (strange attractors), and (ii) the equation’s lack of knowledge of initial conditions translates into unpredictable behavior (chaos). Analysis indicates that indeed all series exhibit chaotic behavior, with strange attractors whose (correlation) dimensions range from 4 to 7. These results support the existence of a low-dimensional chaotic attractor in the lower atmosphere.

1. Introduction

Turbulence has become one of the most elusive problems in physics during the last century. Several approaches, which include those by Von Karman, Kolmogorov and Landau, have failed to simultaneously describe, explain and predict turbulent motion (Stańścić, 1985; Ruelle, 1991). New approaches to the problem have recently emerged due to the advent of chaos theory, in particular through the characterization of “strange attractors” (Ruelle and Takens, 1971). The idea of chaos has been lurking since Poincaré’s work on the stability of nonlinear differential equations. Recently, developments in computer technology and mathematics have allowed an improved understanding of nonlinear chaotic phenomena, leading to better visualization of its solutions and the identification of strange attractors. The first of such attractors was observed in a set of nonlinear deterministic equations (a truncated form of the Navier-Stokes equations) in an attempt to model fluid thermal convection in a gradient-perturbed atmosphere (Lorenz, 1963). This work made clear the intrinsic differences that exist between linear and nonlinear systems, and showed that complex and seemingly random behavior may be obtained from nonlinear deterministic equations.

Nonlinear differential equations may be studied following the evolution of arbi-
trary initial conditions. For fixed times, the resulting coordinates define a point in the phase-space of the system. As time passes, they delineate a trajectory (orbit) in phase-space. The simplest of all behaviors results when all trajectories converge to a single fixed point. In this case, all trajectories are “attracted” to the single steady-state, irrespective of initial conditions. When the equations under study are contractile, i.e., when volumes of arbitrary initial sets decrease as time passes, more sophisticated behaviors may be observed (Lichtenberg and Lieberman, 1983). For these systems, termed dissipative, trajectories in phase-space may converge to infinite (non-periodic) but bounded sets called “strange attractors” (Bergé et al., 1984). These objects derive their names from their fractal nature (Mandelbrot, 1982): they possess a built-in repetitive structure that makes them appear similar when viewed at different scales. When strange attractors exist, extreme sensitivity to initial conditions is typically observed (Moon, 1987). Any two trajectories which start close to one another in phase space, move exponentially away from each other (for small times on the average). This extreme sensitivity to initial conditions defines chaotic motion.

Many types of turbulent flows have been shown to possess chaotic behavior, with a strange attractor occurring on a low-dimensional phase-space (with few coordinates). Among them there are: (i) Couette-Taylor flow (Brandstater et al.,
1983; Mullin and Price, 1989), (ii) Rayleigh-Benard convection (Libchaber, 1987), (iii) fully developed turbulent flows in pipes (Sieber, 1987), (iv) meteorological signals (Romanelli et al., 1988), (v) wind velocities (Tsonis and Elsner, 1989; Pool, 1989), and (vi) rainfall (Rodriguez-Iturbe et al., 1989), among others. All of these strange attractors, living in Euclidean spaces of dimensions less than 10, have been discovered using a powerful theorem proved by Takens (1981). The basis for the procedure is the fact that a single signal (along any given coordinate) contains information of all the variables involved in a given phenomenon liable to be described by a set of coupled nonlinear differential equations. The idea is to reconstruct the underlying attractor by means of successive shifts (delays) of a single observable (signal), such that the obtained attractor preserves the topological characteristics of the underlying process. At this stage, quantification of the fundamental dynamics may be achieved.

The purpose of this work is to study the existence of strange attractors in the turbulence field of the atmospheric boundary layer. For this purpose, the present work reports on an analysis performed on high resolution time series of wind velocities and temperature fluctuations, as measured in and above a deciduous forest in Ontario, Canada (Shaw et al., 1988).
2. Phase-Space Reconstruction from Experimental Time Series

Usually, the system of differential equations which governs a certain phenomenon is unknown, and only a discrete time series $X(t)$ of one of the variables involved is available. In virtue of Taken's theorem, alternative $N$-dimensional reconstructions (embeddings) may be carried out in order to find a suitable characterization of the phenomenon. For different embedding dimensions, pseudo-phase-spaces are constructed via shifts of the given series. Specifically, $N$ coordinates may be obtained considering $X(t), X(t + \tau), \ldots, X(t + (N - 1)\tau)$, where $\tau$ is a delay parameter to be determined.

Three problems arise in practical situations: (i) the accurate definition of the time delay $\tau$, (ii) the selection of the minimum number of data points so that accurate estimations may be obtained, and (iii) the proper determination of the smallest possible number of coordinates, i.e., the minimum embedding dimension. All these concerns remain open questions in the literature of chaos.

2.1. Choosing the Time Delay $\tau$

Accurate definition of the delay $\tau$ is crucial for the proper reconstruction of strange attractors. This work uses the following optimality criteria due to Albano et al. (1988, 1991). The time delay $\tau$ is defined according to
where \( w_1 \) is either the window length of the autocorrelation function of the data (the first lag for which the autocorrelation first passes through zero) or the first local minimum of the autocorrelation function, and \( N \) is the plausible embedding dimension (the number of coordinates) being considered.

2.2. MEASURING CHAOS

2.2.1. The power spectrum

Since the motion of a chaotic signal is non-periodic, its power spectrum (the Fourier transform of its autocorrelation function) does not exhibit defined peaks. Instead, it typically yields a broad-band function, which in general shows an exponential decay with frequency (Bergé et al., 1984; Mayer-Kress, 1985; Sigeti and Horsthemke, 1987), as opposed to an algebraic decay as observed for stochastic processes (Greenside et al., 1982).
2.2.2. Generalized dimensions

As mentioned earlier, a strange attractor is a fractal structure in phase-space. Consequently, its fractal dimension (Mandelbrot, 1982) is one basic measure used to describe it. This fractal dimension determines the number of degrees of freedom of the phenomenon, i.e., the integer part of this dimension plus one is the minimum embedding dimension, viz., minimum number of differential equations needed to describe the motion.

In addition to the fractal dimension, there exists an infinite set of dimensions, $D_q$, which defines other metric properties of the attractor (Hentschel and Procaccia, 1983). These generalized dimensions are defined as follows. Let a strange attractor be covered by $m(\varepsilon)$ boxes of side $\varepsilon$, and let $M$ be the total number of observed points in the attractor. Then, the probability that a point on the trajectory falls on the $i$th box is obtained as the ratio $p_i = M_i/M$, where $M_i$ is the number of points on the orbit that fall on the $i$th box. Now, the infinite set of generalized dimensions is given as:

$$D_q = \frac{1}{q-1} \lim_{\varepsilon \to 0} \frac{\ln \sum_{i=1}^{m(\varepsilon)} p_i^q}{\ln \varepsilon}.$$  

(2)
Notice that different $q$'s weigh the attractor's concentration of points with varying degrees and that $D_0$ simply yields the fractal dimension of the attractor.

In addition to the fractal dimension, the information dimension ($D_1$) and the correlation dimension ($D_2$) are obtained in the limit of Equation (2) as $q$ tends to 1 and 2, respectively. $D_1$ may be expressed as (Farmer et al., 1983):

$$D_1 = \lim_{\epsilon \to 0} \frac{\ln \sum_{i=1}^{m(\epsilon)} p_i \ln p_i}{\ln \epsilon}$$

and hence its name “information” or “entropy” dimension.

The correlation dimension $D_2$ may be shown to give (Grassberger and Procaccia, 1984):

$$D_2 = \lim_{r \to 0} \frac{\ln C(r)}{\ln r},$$

where $C(r)$ is the two-point correlation function defined as:

$$C(r) = \frac{1}{M^2} \sum_{i,j} \theta(r - |\bar{X}_i - \bar{X}_j|),$$
Fig. 2. Two-point correlation functions for selected time series. (a) \( w \) at site 7; (b) \( v \) at site 6; (c) \( w \) at site 5; (d) \( v \) at site 4; (e) \( T \) at site 3; (f) \( u \) at site 2.

where \( \theta \) is the Heaviside step function, and \( M \) is the number of points in the attractor. \( C(\tau) \) counts the number of pairs on the attractor \((X_i, X_j)\), whose distance \(|X_i - X_j|\) is less than \( r \). Intuitively, \( C(\tau) \) accounts for the geometrical correlation that points have within the attractor.

Notice that Equation (4) implies that for small values of \( r \), the two-point correlation function \( C(\tau) \) behaves like a power law:

\[
C(\tau) \sim \tau^{D_2}
\]

Consequently, calculation of the exponent could be obtained from log–log plots of \( C(\tau) \) vs \( \tau \).

The exponent \( D_2 \) is easier to find than \( D_0 \) due to the heavy computational burden incurred in finding fractal dimensions (Greenside et al., 1982). Also, it has been argued that \( D_2 \) more closely characterizes strange attractors due to its intrinsic weighing of points (Grassberger and Procaccia, 1984).

For values of \( q \geq 3 \), Hentschel and Procaccia (1983) give generalized dimensions associated with the two-point correlation function, but now considering triplets, quadruplets, and so on. In principle then, the generalized dimensions \( D_3, D_4, \ldots \),
Fig. 3(a).

Fig. 3(b)
Fig. 3(c).

Fig. 3(d).
can be obtained. It may be shown that these dimensions are ordered: $D_0 \geq D_1 \geq \cdots \geq D_n$, with equality applying only when there is a uniform distribution of points within the attractor.

2.2.3. Estimation of the two-point correlation function and data requirements

The correlation dimension $D_2$ (Equation 4) is one of the main tools used to identify the existence of chaotic dynamics. It has been extensively used in problems related to hydrodynamic experiments, laser systems, neuronal and electroencephalographic signals, epidemiology, climatology, plasmas, etc. All procedures considered in the literature rely on log-log plots of the two-point correlation function $C(r)$ vs. the distance $r$, as introduced by Grassberger and Procaccia (1984).

Deterministic chaos is tentatively identified if the slope of $C(r)$ vs. $r$ converges to a saturation value, for increasing values of the embedding dimension $N$. For deterministic chaotic signals, the slope $D_2$ reaches a maximum due to the low-dimensional nature of the system. As explained before, the obtained saturation dimension, being lower than the fractal dimension of the underlying attractor, is a lower bound for the actual number of nonlinear ordinary differential equations that could be written to describe the data (Moon, 1987). For several systems, however, the fractal dimension $D_0$ and the correlation dimension $D_2$ are very close to each other, and then the value of $D_2$ provides a good estimate of the actual
minimum number of nonlinear differential equations needed to describe the attractor (Moon, 1987).

Although stochastic processes with a power law spectra of the form \( S(w) \approx w^{-\alpha} \) lead to a finite saturation dimension \( D_2 = 2/(\alpha - 1) \) (Osborne and Provenzale, 1989; Pincus, 1991), typically the slope of \( C(r) \) vs. \( r \) increases for stochastic processes as the embedding dimension \( N \) is increased (Grassberger and Procaccia, 1983; Grassberger, 1986). This happens when the coordinates of the phase-space are fully random (e.g., like white noise), leading to points that fill-up space independently of the embedding dimension.

The method by Grassberger and Procaccia has been extensively used in the chaos literature, but some drawbacks have been also reported (Theiler, 1986; Moller et al., 1989). The main limitation of the algorithm is its large computational burden, because it requires computing distances between all pairs of points within the attractor. To circumvent such problems, modifications to the procedure have been introduced by Theiler (1987). This method, named “box-assisted correlation”, takes into account only the shortest distances within the attractor. The attractor is divided into “boxes” of a size \( r_0 \), and then all distances are computed within the boxes (i.e., distances less than \( r_0 \)), and for points in adjacent boxes.
The desired computational savings are realized by considering some – but not all – of the distances greater than \( r_0 \). Theiler’s method will be used in the experimental part of this work.

As mentioned earlier, data requirements represent another constraint in the estimation of the correlation dimension, \( D_2 \). Several investigators have proposed bounds on the actual number of data points needed. Among others, Smith (1988) suggests a safe size of the order of \( 42^{[D_0]} \) data points, where \([D_0]\) is the integer part of the fractal dimension of the set; Ruelle (1990) proposes a size of \( 10^{D_2/2} \) points; while Essex and Nurenberg (1991) argue that \( 2^{D_2}(D_2 + 1) \) points are needed in the reconstructed attractor. These bounds will be checked later with meteorological data.

### Lyapunov exponents

The Lyapunov exponents contain information about the speed at which trajectories exponentially diverge or converge within the attractor. They are related to the expanding or contracting directions in phase-space (Wolf et al., 1986). A chaotic system is characterized by an exponential divergence of nearby initial conditions, and therefore possesses at least one positive Lyapunov exponent. The magnitude of the largest positive exponent (if existent) reflects the time scale on which the
system dynamics become unpredictable (Moon, 1987). Estimation of Lyapunov exponents for an $N$-dimensional dissipative dynamic system requires that one follow the long-term evolution of an infinitesimal $N$-sphere of initial conditions (Wolf et al., 1985). As time passes, the sphere evolves into an ellipsoid. The Lyapunov exponents are defined tracking the principal axes of the ellipsoid. Specifically, the $i$th largest exponent ($\lambda_i$) is defined in terms of the growth rate of the $i$th largest principal axis, $P_i$:

$$\lambda_i = \lim_{t \to \infty} \frac{1}{t} \log_2 \left[ \frac{P_i(t)}{P_i(0)} \right].$$  \hspace{1cm} (7)

Several methods have been proposed to estimate these exponents from experimental time series. Among them, Wolf et al. (1985) presented the first procedure which follows the dynamic separation between nearby pairs of points on the attractor. Landa and Chetverikov (1988) have suggested improvements to this algorithm to shorten its computational time and decrease data requirements. Such
0.220
0.207
0.193
0.180
0.167
0.153
0.140

0 6 12 18 24 30
Time (Min)

Fig. 6(a).

improvements will be used together with the procedure of Wolf et al. (1985) to estimate the largest Lyapunov exponent for the meteorological time series.

Basically, the method employed calculates the average divergence of initially close orbits on the attractor, by considering many points along a trajectory. The algorithm starts by selecting both a reference trajectory on the attractor and a close point on a nearby trajectory. Then, it measures the rate of divergence as both trajectories evolve. As the distance between the two trajectories becomes too large, the algorithm looks for a new nearby trajectory and defines a new small initial separation. Then, averaging over different regions of the attractor is performed, and the largest Lyapunov exponent is estimated through the equation:

$$\lambda_1 = \frac{1}{t_N - t_0} \sum_{k=1}^{N} \log_2 \frac{P_i(t_k)}{P_i(t_{k-1})}.$$  

3. Experimental Analysis

The mathematical tools outlined in the preceding sections were used to test the existence of strange attractors (chaotic dynamics) in the turbulence of the atmospheric boundary layer. Simultaneous measurements of wind velocity and temperature fluctuations at six locations constituted the data set of 24 meteorological time
series. The original data were measured at a deciduous forest experimental site in Ontario, Canada, in an attempt to quantify the turbulent patterns observed in and above the forest (Shaw et al., 1988, 1989; Gao et al., 1989, 1992). Such data included: (i) longitudinal wind velocity \((u)\), (ii) transversal wind velocity \((v)\), (iii) vertical wind velocity \((w)\), and (iv) temperature fluctuations \((T)\).

3.1. Description of Experiments

The set of meteorological time series was gathered using arrays of 3-D anemometers located on two towers separated by a distance of 25 m in which 7 ultrasonic anemometers/thermometers were installed. The seven recording sites were distributed in the following way: sites 1, 2, 3, and 4 at tower number one at heights of 5.9, 10.5, 15.4 and 17.6 m above the ground, and sites 5, 6, and 7 at tower number two at 17.9, 34.2, and 43.1 m above the ground. See Shaw et al. (1988).

The simultaneous series considered in this work each consisted of 18,000 observations measured every 0.1 s (10 Hz) for a total length of 30 min. They were obtained on October 2, 1986 from 2 to 2:30 PM. Skies were cloudless. The Monin–Obukhov length was computed at the forest height of 18 m, and its value of \(-138\) corroborated the presence of unstable atmospheric conditions.
We shall use the 24 (4 x 6) time series recorded at the six highest sites, i.e., 2 through 7. For further information on the time series used, see Poveda (1989).

3.2. SEARCHING FOR CHAOS IN THE ATMOSPHERIC BOUNDARY LAYER

As previously explained in Section 2, the power spectrum, the two-point correlation function, and the largest Lyapunov exponent provide guidelines to test the existence of chaotic dynamics.

First of all, the power spectrum for each of the 24 time series was estimated using the maximum entropy method (Press et al., 1986). Results showed that slopes of the log–log power spectrum agree well with Kolmogorov's −5/3 law. This observation is consistent with other studies related to meteorological phenomena (e.g., MacCready, 1962; Bath, 1974). For illustration, Figure 1 presents a portion of the power spectrum of the vertical wind velocity at location 6 (w6). As the power spectra do not exhibit any preferred frequency, chaotic behavior can not be ruled out from the analysis.

Phase-space reconstruction was performed employing Equation (1) to find the time delay \( \tau \). Once reconstruction was carried out, computation of the two-point correlation function for the set of 24 meteorological time series was performed using Theiler's method (1987). Embedding dimensions used for the pseudophase-
space ranged from 2 through 12. For all cases, convergence of the slopes of log $C(r)$ vs. log $r$ (found via linear regression) was obtained. This could be seen in Figures 2a–f, which in order show the two-point correlation functions for the series w7, v6, w5, v4, T3, and u2, as the embedding dimension $N$ is varied. Figures 3a–f present the embedding dimension, $N$, vs. correlation dimension, $D_2$, for the time series considered in Figures 2. Also included in Figures 3, as squares, are the correlation dimensions that would be obtained from purely stochastic processes. Notice that the computed dimensions saturate as $N$ increases. This fact indicates the existence of low-dimensional attractors, and deterministic chaos, whose confirmation requires positive Lyapunov exponents.

Table I includes the correlation dimensions found for the different phenomena. The orders of magnitude obtained in this work agree well with those previously found by Tsonis and Elsner (1989) and Pool (1989) for wind velocities at other locations. Although the very stringent data requirements set forward by Smith (1988) are not valid for any of the time series analyzed, both conditions suggested by Ruelle (1990), and by Essex and Nurenberg (1991) are satisfied by all data sets. Observe that Kolmogorov’s $-5/3$ law implies for a stochastic process with power law spectra a correlation dimension of 3. Because all correlation dimensions

![Fig. 6(d).](image-url)
in Table I are above 3, there is indeed no evidence that such data may be represented by such a stochastic process.

Notice that although sites 4 and 5 are located at about the same elevation on separate towers, their correlation dimensions were not equal. This observation, based on a single data set, does not contradict the good agreement in Reynolds stresses that Shaw et al. (1988) reported over a variety of stability conditions at those elevations. Even though there are no obvious trends on all the obtained dimensions, it is worth noticing that correlation dimensions for velocities do increase for elevations at and above the forest canopy (sites 4, 6, 7, or, 5, 6, 7), indicating qualitatively more turbulent behavior for higher elevations. Inside the forest at the first tower (2, 3, 4), there are no consistent patterns. As seen in Figure 4a, there is non-monotonic behavior in correlation dimensions for velocities in the horizontal plane, while they decrease with height for vertical velocities. This overall picture resembles the patterns observed by Shaw et al. (1988) regarding horizontal correlations ($u_w$) vs. height, with higher negative correlations above the forest, and variable negative correlations inside the forest, see Figure 4b. Also, mirror images of the observed profiles on correlation dimensions exhibit the same qualitative trends of relative intensities of turbulence (a coefficient of variation defined by dividing the velocity standard deviations by the cup wind speed), as reported by Shaw et al. (1988), Figure 4c. Whether or not these structures could be understood jointly remains an open question. Certainly, a chaotic analysis of such surrogates of turbulence (and others like Reynolds stresses, heat fluxes, etc.) may provide additional information, specially if alternative stability conditions for different foliage coverages are considered.

Figure 5 shows the observed ramp structure of the temperature measurements at sites 1, 2, 3, 5, 6, and 7, as reported by Gao et al. (1989). The ramps are more clearly defined for locations inside the forest (below 18 m). The relative unpredictability of temperature fluctuations for different elevations is nicely captured by the correlation dimensions in the last row of Table I. Observe that as one moves upward, the correlation dimensions increase (except for the highest site), indicating more erratic behavior and the need for higher order sets of differential equations. Although the pattern is broken for the last site, notice that the data complexity captured by the eye is entirely consistent with the obtained

<table>
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<tr>
<th>Site phenomenon</th>
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<th>3</th>
<th>4</th>
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<td>$u$</td>
<td>4.4</td>
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<td>5.7</td>
<td>6.4</td>
</tr>
<tr>
<td>$v$</td>
<td>4.0</td>
<td>4.4</td>
<td>3.7</td>
<td>4.9</td>
<td>5.7</td>
<td>6.2</td>
</tr>
<tr>
<td>$w$</td>
<td>4.3</td>
<td>4.1</td>
<td>3.6</td>
<td>4.1</td>
<td>6.7</td>
<td>6.8</td>
</tr>
<tr>
<td>$T$</td>
<td>4.5</td>
<td>5.0</td>
<td>5.3</td>
<td>5.8</td>
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numbers. Correlation dimensions are therefore valuable surrogates for qualitative data comparisons.

To corroborate the existence of chaotic behavior, the largest Lyapunov exponent ($\lambda_1$) was computed for the meteorological series corresponding to the three highest sites, i.e., 5, 6, and 7. The analysis was carried out using the algorithm by Wolf et al. (1985), modified to include the improvements suggested by Landa and Chetverikov (1988). As seen on Table II, all sites considered are found to lead to positive Lyapunov exponents, thus confirming the existence of chaotic behavior. Figures 6a–d show the evolution of the largest exponent throughout the attractor for, in order, the time series $u_6$, $T_6$, $u_5$, and $v_5$. Notice that all series result in similar numbers, with no obvious trends for different heights.

**4. Conclusions and Further Research**

Low-dimensional strange attractors, whose correlation dimensions range from 4 to 7, have been identified in the turbulence of the atmospheric boundary layer in and above a forest in Ontario, Canada. 24 time series of wind velocities and temperature fluctuations, sampled every 0.1 s for a total of 30 minutes under unstable atmospheric conditions, were used in the analysis. Chaotic dynamics were also confirmed for the turbulent field through power spectrum and Lyapunov exponent calculations.

The range obtained on correlation dimensions is consistent with the work of Tsonis and Elsner (1989) and Pool (1989) dealing with wind velocities at other sites. These dimensions were found to be good surrogates of erratic behavior, which matched general trends of turbulence-related characteristics (relative intensities of turbulence and general patterns of coherent structures in temperature records, as reported respectively by Shaw et al. (1988) and Gao et al. (1989)). Due to this observation, it is proposed that a chaotic analysis be performed on those turbulence-related characteristics and other turbulence surrogates like Reynolds stresses and normalized intensities of turbulence, in an attempt to further quantify them and study their interrelations to the dimensions reported here. Also it is suggested that the study be made under alternative atmospheric stability conditions and different foliage coverages.
Once chaotic behavior of low-dimensionality is identified and confirmed, the next step is to develop appropriate sets of nonlinear differential equations for short-term modeling. In this context, further work may be carried based on the works of Crutchfield and McNamara (1987), Abarbanel et al. (1990), and Sugihara and May (1990).

This study brings further light to the important open issues pertaining to the existence of a chaotic climatic attractor, as discussed in the works of Nicolis and Nicolis (1984), Grassberger (1986), Fraedrich (1986), Tsonis and Elsner (1989), and Lorenz (1991), among others. Certainly, the results presented here are consistent with the hypothesis that low-dimensional deterministic chaos is present in the lower atmosphere.

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