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Wind Velocity Fluctuations Time Series Analysis

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Abstract: - The temporal structure of wind was investigated by means of temporal correlations of 10-min wind time series measured over a period of one year (2004). The Hurst exponent (*H*), one of a number of methods to identify the existence of long-range correlations in experimental data, has been applied to quantify self-similarity scaling and correlations in the mesoscale temporal range. The Hurst exponent can be calculated by several different algorithms, each of which has particular advantages and disadvantages. One of these methods is via Structure Functions (SF's) that has not yet been widely used in wind time series. In this work, SF method has been used in measured wind fluctuation for each month of the studied year. The results point out a multiscaling or scaling behavior, depending on the month analyzed, from 10 minutes till 3 hours, approximately, with a significant anti-persistence character.

Key-Words: - Wind, Time Series, Scaling, Multifractal, Structure Function.

1 Introduction

Many time series show pronounced cyclic trends. For example, daily temperature data follow an annual cycle whose magnitude overwhelms other fluctuations; rainfall data in many areas undergoes a similar annual cycle of similar magnitude as well as wind velocity data (*w*)[11].

For most practical applications, such as engineering and meteorology one mainly distinguishes between large scale variations such as diurnal, weekly and seasonal changes and variations on small scales often referred to as atmospheric turbulence or gustiness [4]. The existence of a mesoscale gap as proposed by Van der Hoven [21], which divides micro, and macro scales in a more rigorous way has strongly been debated in recent years [6, 13].

The study of *w* is aimed at greenhouse control (heating and ventilation), since wind velocity influences both types of control. Wind increases heat losses in winter nights, so it is of interest to regulate the heating as a function of wind-speed (*w*). With respect to ventilation, the opening of the windows must be reduced with high values of wind velocity [9]. This kind of relationship makes the identification of patterns in the wind's behavior very interesting. It is therefore desirable to compare the wind speed on a given date to the average of the wind speed on that date [1, 2, 19].

In the last few decades there has been an increasing recognition that multiplicative cascades combined with multiscaling analysis represent extremely useful tools for characterizing a variety of geophysical signals [3, 5, 19, 20].

Cascade model generate signals by dividing an interval assigned a single value into an integer number of parts, and assigning each new interval a new value, usually some random ratio of the initial value. This process is then iterated on each new interval, and so on. The resulting data can be described by the multifractal formalism [7, 8] and can be characterized with the use of multiscaling analysis, which determines the dependence of the statistical moments on the resolution with which the data are examined [15]. In some way, Frich and Parisi [7] introduced the idea to understand many geophysical time series data as a chaotic process.

A stochastic fractal representation of wind-speed was introduced by Schmitt et al. [17] via the notion of universal multifractals [12]. Their idea is to represent time series as a realization of a Levy process and parameterize it via its codimension function. Whether or not there is a "universal multifractal model" remains a relevant topic of search [e.g., 11, 13, 14]. Even though reasonable looking simulations having intermittency, as found in wind-speed and rainfall, may be obtained a demand for reliable predictions has been growing lately [18].

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This type of analysis has important implications on the understanding of wind-speed patterns and shows this variable to be more heterogeneous than is usually modeled. The aim of this work is to study the multifractal nature of this series and to fully characterize the dynamical system that supports it. In this way, it is possible to simulate at high resolution (interval of 10 minutes) monthly wind-speed fluctuations series.

2 Multifractal Analysis

2.1. Structure Function

For nonstationary processes, *w(t)*, with stationary increments, the Structure Function (*M*) of order q is defined as the q-th moment of the increments of *w(t)* by the follow equation:

$$M_q(t) \equiv \left\langle \left| w(t_i + t) - w(t_i + t) \right|^q \right\rangle \tag{1}$$

Where i denotes the ith data point, and $\langle \ \rangle$ denotes the ensemble average. Structure Functions are generalized correlation functions, which is particularly evident from Eq. (1) for the case of q=2. In general, q may be any real number not just integers, and can even be negative. However, there are divergence problems inherent to the negative-order exponent so that computations are best restricted to positive real number [5]. If the process *w(t)* is scale-invariant and self-similar or self-affine over some range of time lags $t_1 \le t \le t_2$, then the qth-order structure function is expected to scale as:

$$M_q(t) = C_q t^{z(q)} \tag{2}$$

where C_q can be a function of t which varies more slowly than any power of t, and $z(q)$ is the exponent of the structure function. $z(q)$ is a monotonically non-decreasing function of q if *w(t)* has absolute bounds [8, 14]. Therefore, a hierarchy of exponents can be defined using $z(q)$:

$$H(q) = \frac{z(q)}{q} \tag{3}$$

Where H(q) is the Hurst exponent (or self-similarity scaling exponent) [5]. Calculation of H(q) allows the straightforward identification of persistence, or long-time correlation, as well as the stationary/nonstationary and monofractal/multifractal nature of the data [13]. Following the original work of Hurst [10], $0.5 < H < 1$ indicates persistence, while $H = 0.5$ indicates an uncorrelated random process, and $0 < H < 0.5$ can be taken to indicate anti-correlation. Stationary processes have scale-independent increments and $z(q) = H(q) \equiv 0$, due to the invariance under translation. Processes with a linear $z(q)$ (or a constant *H(q)*) are non-stationary and monofractal, otherwise they are non-stationary and multifractal.

In this case the value of q varies from 1 to +12 with an increment of 1. The numbers of points used in each regression line, obtained from Eq. (2) taking natural logarithms, for a fixed q to estimate $z(q)$ was always 9 points.

2.2. Power Spectra

In the analysis of real data, the statistics of the time series *w(t)* play a crucial role. As discussed by several authors [5], non-stationary scale-invariant, self similar processes are expected to have power spectra, $S(w)$ that exhibit power law scaling as:

$$S(w) \propto |w|^{-b} \tag{4}$$

According to the Wiener-Khinchine theorem [16], the second order structure function is in Fourier duality with the power spectrum. Thus the relation between b and *H(q=2)* for a monofractal process is given by:

$$1 < b = 2H(q=2) + 1 < 3 \tag{5}$$

Since b and $\frac{z(q)}{H(q=2)}$ are independently computed from the power spectrum and structure function from the same data, Eq. (5) can be used to verify any assumptions of a nonstationary self-similar process with stationary increments. In contrast, for a stationary self-similar processed, the Wiener-Khinchine theorem relates b with *H(q=2)* as:

$$-1 < b = 2H(q=2) - 1 < 1 \tag{6}$$

2.3. Data

Data used in this study was acquired from the climatic station of the Dpto. de Producción Vegetal: Botánica y Protección de Cultivos, placed in the

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experimental fields of the Agricultural School of Madrid. Every ten minutes, the station recorded mean values of the wind velocity in m/s. This data was kindly furnished by Prof. Jose Luis García, from Polytechnic University of Madrid, Department of Rural Engineering. We used times series data from 2004 (Fig. 1). Thus we handle in each yearly analysis a series of 105.408 data points, and in the monthly analysis a minimum of 4.176 values (February) and a maximum of 4.464.

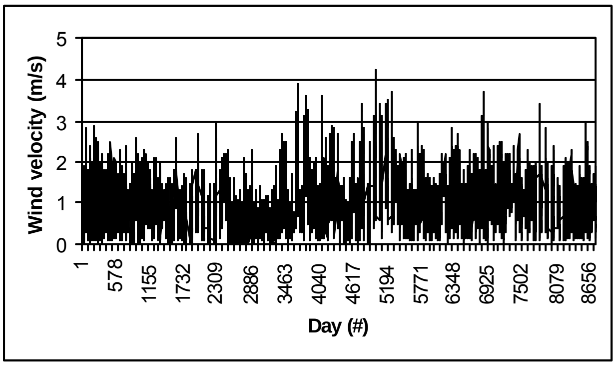

Figure 1. Wind velocity time series during March and April of 2004.

3 Results and Discussion

The determination of $z(q)$ was done for each month separately. In Fig. 2 the results for February of 2004 year are showed. This month presented the worst case of the months studied. For q=2 only the first nine points showed a linear pattern, but for higher q values the number of points that followed an straight line was lower.

Because the aim of this study was to compare the structure presented in the time series, the analysis was done with the same methodology in the regression analysis, taking nine points, as it was the optimal case for almost of the time series.

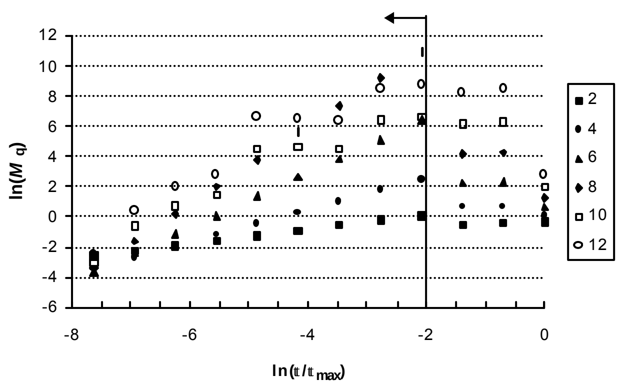

Figure 2. Structure Functions (M) for q= 2, 4, 6, 8, 10 and 12 for February of 2004. The arrow indicates the selected range to calculate the slope.

The $z(q)$ and *H(q)* functions are showed in Fig. 3 for three moths that represent all the cases found.

February shows a different behavior from the other months, however the q values used are much higher that it is normally found in the literature. July shows a clear multiscaling pattern that can be checked with the power spectrum obtained for this month (figure 4). Based in this plot β can be obtained given a value of 1.81, in accordance with the *H(q=2)* estimated.

The last case showed is December. It has an anti-persistent character but the almost *H(q)* constant value reveal a fractal nature and not multifractal.

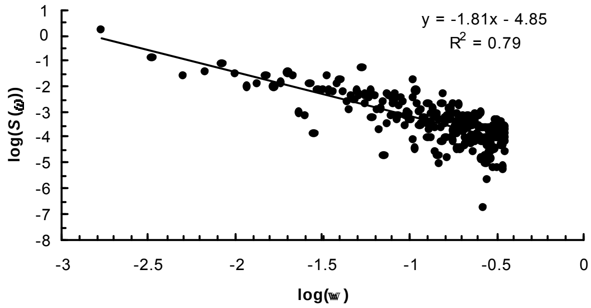

Figure 4. Power spectrum(S(ω)) of wind fluctuations corresponding to July of 2004.

4 Conclusion

Over the last ten years there has been evident in the literature a growing interest in fractal and multifractal analysis of time series including winds.

In terms of modeling wind time series, and the processes they reflect, it is important that we have means of usefully characterizing this multiscale heterogeneity, being one of them Structure Functions. Base on this modeling characterization and simulation of wind fluctuations can be possible and realistic.

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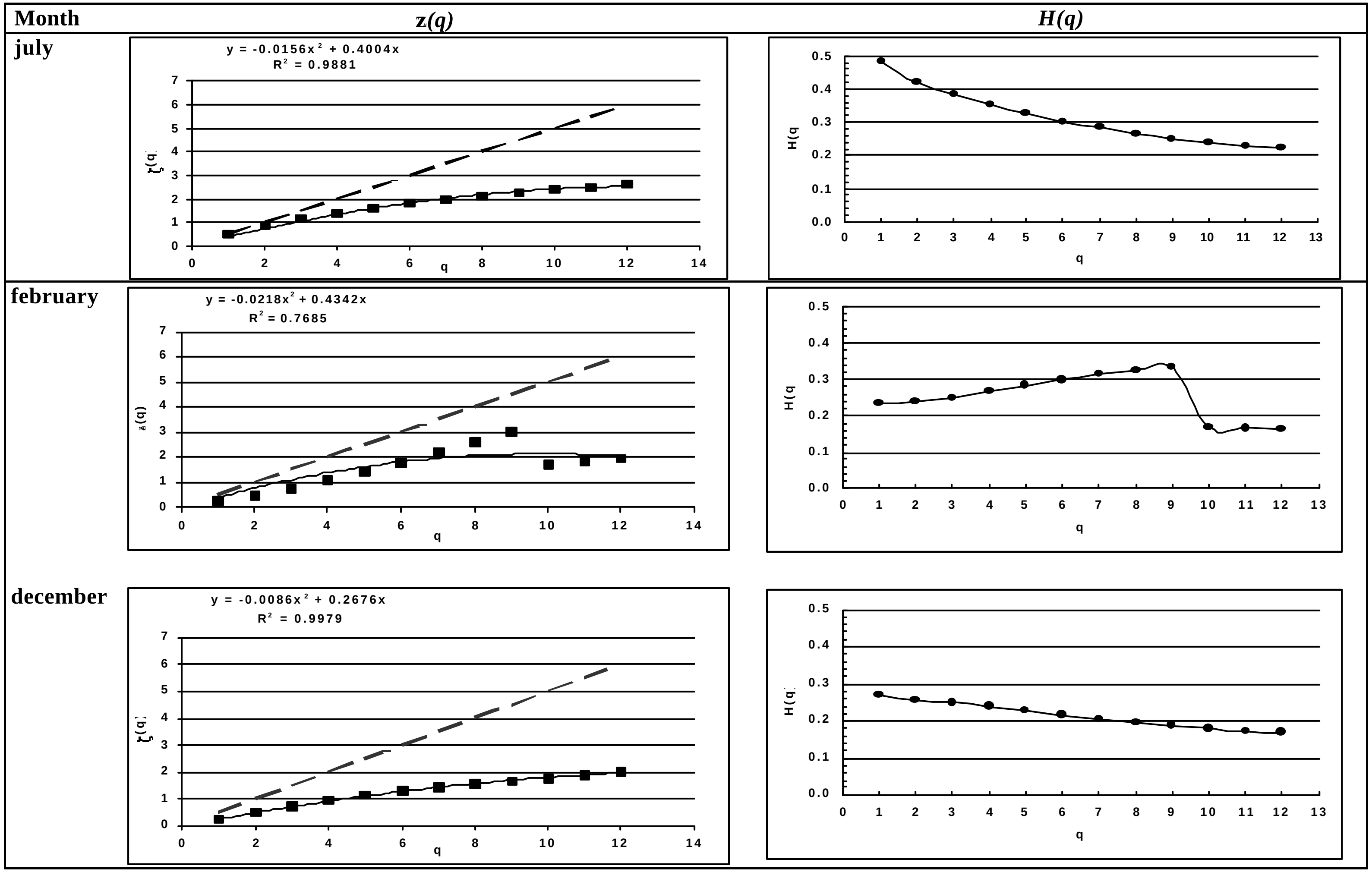

Figure 3. *z (q) and the corresponding H(q) function for three different months of 2004. Dot lines correspond to a z (q) function when H(q) is constant with a value of 0.5 (random process).*