Multiscaling Analysis of Wind Velocity Time Series

A M TARQUIS, M.T. CASTELLANOS, M.C. MORATÓ and J.M. ANTÓN Dpto. de Matemática Aplicada a la Ingeniería Agronómica. E.T.S. de Ingenieros Agrónomos - U.P.M. Ciudad Universitaria s.n. 28040 Madrid. SPAIN

Abstract: - A multifractal analysis of wind time series has been applied for two different years, 2003 and 2004. These values have been recorded each ten minutes, showing intermittency in their pattern. The MFA was performed for each month of each year and also for each whole year. The analysis shows a multiscaling structure in consistence with other authors. Differences in the multifractal spectrum are found among months and practically non between the two years. These differences are localized in the right side of the spectrum, pointing out that further research should be done on the scaling behavior of events of lower frequencies that correspond to such part of the spectrum. Base on this type of modeling, realistic simulations for green house systems are possible.

Key-Words: - wind-speed, time series, probabilistic measure, multifractal analysis.

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*).

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 [8]. 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].

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 [5].

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 [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. In some way, Frich and Parisi [8] 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. [16] via the notion of universal multifractals [11]. Their idea is to represent time series as a realization of a Levy process and parameterize it via its codimension function, basically the left portion of the multifractal spectrum [e.g. 7, 15]. Whether α not there is a "universal multifractal model" remains a relevant topic of search [e.g., 19, 10]. Even though reasonable looking simulations, having intermittency as found in wind-speed and rainfall, may be obtained, it is difficult to find conditional simulations with such an approach. A new procedure for the quantification of geophysical phenomena was introduced by Puente [13, 14, 15] and it is the fractal-multifractal approach (FM). However, fewer works have been published applying deterministic fractal interpolating functions or FM representation. The basic idea of the FM approach is to think of intricate patterns as projections of fractal functions, which go through simple multifractal measures, and consequently this methodology has a deterministic nature [13, 14, 15].

Such 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 support it. In this way, it is possible to simulate at high resolution (interval of 10 minutes) monthly wind-speed series.

2 Multifractal Analysis

2.1. Theory

In this work wind velocity (*w*) is studied in terms of the percentage of frequency distributed at different times. Thus, one value may be taken as the *w* fraction, p_i , in a certain time "i". The support of this measure is the set of real numbers corresponding to t values. Thus, p_i can be interpreted as the probability of finding velocities of a certain value within interval "i".

The structure of this probability measure p on the segment $(t_0, t_f]$ may be defined by the scaling relationship:

$$p \propto \boldsymbol{d}^{\mathbf{a}} \ as \boldsymbol{d} \to 0 \tag{1}$$

Where the scaling exponent α is the so-called Lipschitz-Hölder exponent, and δ is the length of the subintervals in which the total segment is divided. However *p* is spread over the interval in such way that the concentration of velocities varies widely and a different behavior is observed in different positions (i), that is:

$$p(i) \propto \boldsymbol{d}^{\boldsymbol{a}(i)} \, as \, \boldsymbol{d} \to 0 \tag{2}$$

which defines an spectrum of values of α that corresponds to different spatial positions i. Hence the singularity exponent α is a function of the position "i" , many sites "i" may share the same exponents when a regular covering of size δ is chosen. Therefore, let $N(\alpha,\delta)$ be the number of sites "i" that share the same measure p_i , that presents the following scaling relationship:

$$N(\boldsymbol{a},\boldsymbol{d}) \propto \boldsymbol{d} - f(\boldsymbol{a}) \, as \, \boldsymbol{d} \to 0 \tag{3}$$

Where $f(\alpha)$ -singularity spectrum describes the statistical distribution of the singularity exponent α ,

or in other words, counts how often specific values α of the singularity strengths occur [7].

2.2. Methodology

There are several ways to calculate the $f(\alpha)$ singularity spectrum being one of them the methods of moments explained by Evertsz & Mandelbrot (1992) [6].

To search for a multifractal structure, following the general methodology of Evertsz&Mandelbrot (1992) [6] and Feder (1988) [7], and the specific techniques of Chhabra&Jenssen (1989) [4] and Meneveau&Sreenivasan (1989) [12], the wind velocity data (w) was divided into n intervals of size δ (n(δ)) in the value of D. Thus, the mean value of D in interval i is D(δ) and the frequency of the data points in that box is $\rho_i(\delta)$, both being dependent of the interval size δ . A normalized measure is defined by:

$$\hat{\mathbf{i}}_{i}(\mathbf{q}, \ddot{\mathbf{a}}) = \frac{\mathbf{r}_{i}^{q}(\mathbf{d})}{\sum_{i=1}^{n(\ddot{\mathbf{a}})} \mathbf{r}_{e}^{q}(\mathbf{d})}$$
(4)

Then the coarse Hölder exponent

$$\boldsymbol{a}(q) = \lim_{\boldsymbol{d} \to 0} \frac{\sum_{i=1}^{n(\boldsymbol{d})} \boldsymbol{m}_i(q, \boldsymbol{d}) \log[\boldsymbol{m}_i(1, \boldsymbol{d})]}{\log \boldsymbol{d}}$$
(5)

and the Hausdorff measure

$$f(q) = \lim_{a \to 0} \frac{\sum_{i=1}^{n(a)} i_i(q, a) \log[i_i(q, a)]}{\log a}$$
(6)

are calculated for a series of diminishing interval sizes δ for each series of values of q. A relation between f and α is thus established, with q as a parameter.

In this case the value of q varies from -2 to +10 with an increment of 0.2. The numbers of points used in each regression line, for a fixed q, was always 10 points. In other words the number of subintervals achieved was 210 in the monthly study.

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 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 and 2005 (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.

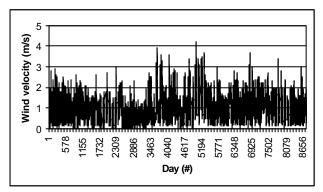


Figure 1. Wind velocity time series during March and April of 2003.

3 Results and Discussion

The determination of the multifractal spectrum $(f(\alpha))$ was done for each month separately and also for each year. 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 needed to get the spectrum. In Fig. 2 the results for 2003 year are showed.

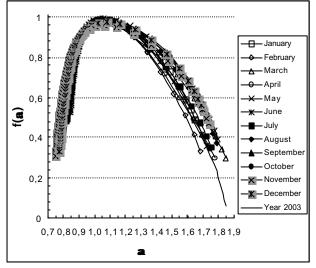


Figure 2. Mulftifractal spectrum for each month and multifractal spectrum of the whole year 2003.

The convex function $f(\alpha)$ varies between months pointing out the different richness of the studied structure.

One way to see the variations in complexity between months is to plot the amplitude (α_{mar} - α_{min}) reached by the spectrum in each one [8, 17, 18]. The months that show a lowest complexity are February 03, January 03, July 03 and April 03. The spectrum for the whole year 2003 is contained in the range of the month's spectrums.

The same results are obtained for 2004 year. However the months that show higher complexities are different than for 2003 year (see Fig. 3).

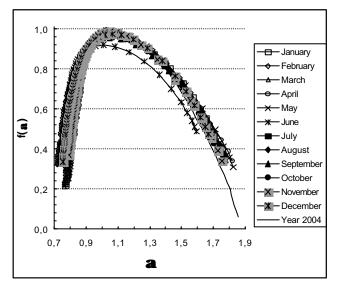


Figure 3. Mulftifractal spectrum for each month and multifractal spectrum of the whole year 2004.

In 2004 year, it is June that shows the narrowest spectrum. It is also observed that this month presents a higher frequency of nulls values as it is reflected by the fact that for q=0 the f value is 0.9.

The overall structure of these time series for each year is almost the same (Fig. 4). The changes in amplitude of the $f(\alpha)$ singularity spectrum are statistically non significant. However, the scaling behavior at the right side of the spectrum (for negative q values) can be differentiating.

In all the multifractal spectrum showed the differences were found always in the range of negative of q values, but in the positive q values they are very closed pointing out a very similar scaling. In many works cited here, non has focus in the differences of the spectrum in wind time series.

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.

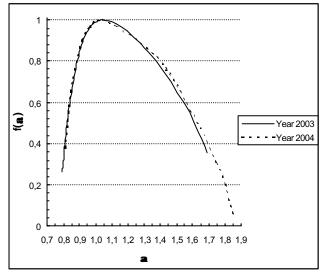


Figure 4. Mulftifractal spectrum for each year taking all the data series.

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 multifractal measures. Base on this modeling characterization and simulation of the time series can be possible and realistic.

References:

- Bailey, B.J. Constraints, limitations and achievements in Greenhouse Natural Ventilation. *Acta Hort*. (ISHS), Vol. 534, 2000, pp. 21-30.
- [2] Bailey, B.J. and Chalabi, Z.S. . Improving the cost effectiveness of greenhouse climate control. Computers and Electronics in Agriculture, Vol. 10, No. 3, 1994, pp. 203-214.
- [3] Bras, R. and Rodríguez-Iturbe, I. . Random Functions and Hydrology, 2nd Ed. . Dover Publications, Inc., New York, 1993.
- [4] Chhabra, A.; Jensen, R. V. . Direct Determination of the $f(\alpha)$ Singularity Spectrum. Physical. Review. Letters., Vol. 62, No. 12, 1989, pp. 1327-1330.
- [5] Davis, A.; Marshak, A.; Wiscombe, W. and Cahalan, R. . Multifractal Characterisations of Nonstationary and Intermittency in Geophysical Fields: Observed, Retrieved, or Simulated. J.

Geophys. Res., Vol. 99, No. D4, 1994, pp. 8055-8072.

- [6] Evertsz, C. J. G.; Mandelbrot, B.B. Multifractal Measures. In *Chaos and Fractals: New Frontiers* of Science; Peitgen, H., Jurgens, H. and Saupe Springer-Verlag D., Eds.: New York, 1992; pp. 921-953.
- [7] Feder, J. *Fractals*; Plenum Press: New York, 1989.
- [8] Frisch, U and Parisi, G. A Multifractal Model of Intermittency. In *Turbulence and Predictability in Geophysical Fluid Dynamics and Climate Dynamics*. North-Holland, Amsterdam, 1985, pp. 84-88.
- [9] García, J.L.; de la Plaza, S.; Navas, L.; Benavente, R.M.; Luna, L. . Evaluation of the Feasibility of Alternative Energy Sources for Greenhouse Heating. J. Agric. Eng. Res., Vol. 69, No. 2, 1998, pp. 107-114.
- [10] Lauren, M.K.; Mendabe, M. and Austin, G.L. . Analysis and simulation of surface-layer winds using multiplicative cascade models with selfsimilar probability densities. Boundary-Layer Meteorology, Vol. 100, No. 2, 2001, pp. 263-286.
- [11] Lovejoy, S. and Schertzer, D. Multifractals, universality classes, and satellite and radar measurements of cloud and rain fields. J. Geophys. Res., Vol. 95, No. D3, 1990, pp. 2021-2034.
- [12] Meneveau, C. & Sreenivasan, K.R. . Measurement of $f(\alpha)$ from scaling of histograms, and applications to dynamical systems and fully developed turbulence. Phys. Lett. A, Vol. 137, No. 3 ,1989, pp. 103-112.
- [13] Puente, C.E. A deterministic geometric representation of temporal rainfall: Results for a storm in Boston. Physics Letters A, Vol. 161, No. 5, 1992, pp. 441-447.
- [14] Puente, C.E. and Klebanoff, A.D. Gaussians Everywhere. Fractals, Vol. 2, No. 1, 1994, pp. 65-79.
- [15] Puente, C.E. and Obregón, N. A deterministic geometric representation of temporal rainfall: Results for a storm in Boston. Water Resource Research, Vol. 32, No. 9, 1996, pp. 2825-2839.
- [16] Schmitt, F; Schertzer, D.; Lovejoy, S. and Brunet, Y. . Estimation of universal multifractal indices for atmospheric turbulent velocity fields. Fractals, Vol. 1, No. 3, 1993, pp. 568-575.
- [17] Tarquis, A.M.; Giménez, D.; Saa, A.; Díaz, M:C. and Gascó, J.M. . Scaling and Multiscaling of Soil Pore Systems Determined by Image Analysis. In: Scaling Methods in Soil Physics, Pachepsky, Radcliffe and Selim Eds., CRC Press, 2003.

- [18] Tarquis, A.M.; Losada J.C., Benito, R. and Borondo, F. . Multifractal Analysis of the Tori Destruction in a Molecular Hamiltonian System. Phys. Rev. E , Vol. 65, No. 1, 2002, pp. 0126213(9).
- [19] Tuck, A.F.; Hovde, S.J. Fractal behavior of ozone, wind and temperature in the lower stratosphere.. Geophysical-Research-Letters, Vol. 26, No. 9, 1999, pp. 1271-1274.