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Multifractal analysis of the time series of daily means of wind speed in complex regions

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ABSTRACT

In this paper, we applied the multifractal detrended fluctuation analysis to the daily means of wind speed measured by 119 weather stations distributed over the territory of Switzerland. The analysis was focused on the inner time fluctuations of wind speed, which could be linked with the local conditions of the highly varying topography of Switzerland. Our findings point out to a persistent behaviour of almost all measured wind speed series (indicated by a Hurst exponent larger than 0.5), and to a high multifractality degree indicating a relative dominance of the large fluctuations in the dynamics of wind speed, especially on the Swiss Plateau, which is comprised between the Jura and Alps mountain ranges. The study represents a contribution to the understanding of the dynamical mechanisms of wind speed variability in mountainous regions.

1. Introduction

Wind has been gaining an increasing attention in the context of renewable energy because it represents one important substituent to conventional fuels that should play a major role in the future energy mix [1]. In fact, wind power has the advantage to be widely produced (in the three consecutive years, from 2013 to 2015, the world total wind capacity grew up more than 10% [2]) with little environmental pollution, becoming economically competitive as a type of clean energy source capable of withstanding environmental damage and avoid future crises [3].

In mountainous regions like the Alps, wind speed highly changes not only in time but also in space. Topography, in fact, influences strongly the wind speed [4,5]. Ridge crests, deep valleys, or other irregular landscapes are important orographic features that can exert an influence on boundary layer flows [6]. The Alps are characterized by many local climatic phenomena, natural channelling effects, and thermally induced circulations that make, for instance, wind speed very high at one location but very slow in a near valley, revealing a large variability and discontinuous character within small areas, and making the spatial interpolation of wind speed quite arduous [7]. The analysis of wind speed within the atmospheric boundary layer is always challenging, since it represents a largely fluctuating and non-linear component of atmospheric flows, whose space-time variability can be high [6]. In addition, the modelling of wind speed and extreme events, as well as the regionalisation schemes of wind speed and direction is rather difficult [8], due to the presence of many turbulence effects and roughness factors [9]. However, some methods have been developed to overcome the problems related to the regionalisation of wind speeds [6,10–13], by using correction factors related to topography (slope angle, altitude, land-form characteristics) that, added to the calculation of wind speed, have enabled a better adjustment of the results with the observations.

Several studies have been performed on the wind speed field over the territory of Switzerland [13,14], which is characterized by a topographically complex terrain. Etienne et al. [6] applied the Generalized Additive Models (GAMs) to regionalise wind speeds measured at the Swiss weather stations by means of a number of physiographic parameters. They succeeded in providing reliable wind predictions on the basis of the 98th percentile of the daily maximum wind speed, and found a dependence of wind speed upon the altitude and roughness of the mountain shapes. Jungo et al. [14] applied the Principal Component Analysis (PCA) and the Cluster Analysis (CA) to several Swiss meteorological stations. They clustered these structures based on their daily gust factors, depending on the weather type. As a result, the obtained clusters of stations, whose spatial distribution depended on the complexity of terrain, exhibited a comparable variability to the daily gust factor and to their response to the weather forcing. Weber and Furger [15] applied an automated classification scheme to one year wind data and found 16 distinct near-surface wind flow patterns, whose

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knowledge is important because they can form intricate patterns such as large-scale winds and locally forced wind systems interplay. Robert et al. [16] applied general regression neural networks (GRNN) as a non-linear regression method to interpolate monthly wind speeds in complex Alpine orography, using as training data those coming from Swiss meteorological networks to capture the relationships between topographic features and wind speed.

In this study, we aim at analysing the time series of daily mean of wind speed recorded by a wide monitoring network covering all the territory of Switzerland. Because of the complexity of the terrain, related to the large variability of topographic conditions that characterize Switzerland, wind speed is featured by a complex time dynamics. In order to investigate the dynamical properties of wind speed time series, we use the multifractal detrended fluctuation analysis (MFDFA) to identify correlations, persistence, intermittency, and heterogeneity.

Since the investigation of multifractal behaviour in wind speed has been becoming an important topic only recently, just a few studies have been carried out so far. Kavasseri and Nagarajan [17] showed that the multifractality found in four time series of hourly means of wind speed in USA could be explained by fitting the data with a binomial cascade multiplicative model. Telesca and Lovallo [18] found that the multifractality of the wind speed series recorded at several heights from the ground from 50 to 213 m was due to the different long-range correlations in small and large speed fluctuations. Fortuna et al. [19] applied the MFDFA to several hourly wind speed series in Italy and USA and found that the multifractal width ranged in a quite close interval of values between 0.39 and 0.59. De Figueiredo et al. [20] found that the mean and the maximum of four wind speed time series in Brazil were all persistent, but the maximum was more multifractal than the mean. Piacquadio and de La Barra [21] suggested the use of some key multifractal parameters of wind speed as local indicator of climate change. Telesca et al. [22] analysed the spectral and the multifractal characteristics of several wind speed time series in Switzerland, they found cyclic components with period of 1 day and 12 h. These cyclic components are linked with the daily cycle of temperature and pressure, along with persistence and multifractal characteristics at large timescales, but anti-persistence and monofractal behaviours at smaller ones. The multifractal analysis has been used also in complex networks; for instance Jalan et al. [23] analysed the scaling behaviour of edges of networks.

In our paper, we apply the MFDFA to a large dataset of 119 wind speed time series, measured by weather stations belonging to the meteorological network that covers the whole territory of Switzerland. Our aim is to investigate the spatial variability of the persistence, and the multifractal features of wind speed in Switzerland; and to find possible relationship with its topography. In order to analyse only the inner fluctuations of wind speed that are not affected by seasonal cycles, we ignored the trend and seasonal of the time series and focused our attention only on the remainder (residual) obtained after the decomposing of the time series.

2. Data and exploratory analysis

The data used in this work are provided by the Federal Office of Meteorology and climatology of Switzerland, which manages a wide network of meteorological stations covering the entire Swiss territory more or less homogeneously at different altitudes. Fig. 1 shows the location of the wind stations and the three Swiss regions (Jura, Plateau and Alps) delimited by SwissTopo (Swiss Federal Office of Topography) based on geological and geomorphological features. This data were used by Vega Orozco et al. [24] to characterise the spatial distribution pattern of the population in Switzerland using fractal and multifractal tools.

In this work, the raw data consist of high frequency (10-min sampling time) wind speed series, collected by 119 stations, during the period between 2012 and 2016 (Fig. 2 shows, as an example, some wind speed time series). We analysed the daily means of wind speed in order to remove the periodicity of one day and 12 h [22].

Because of the complexity of the data, we performed an exploratory analysis in order to identify the probability distribution that better describes wind speeds. We considered the three distributions that are mostly used to model wind speed. Table 1 illustrates for each distribution its probability density function and the corresponding parameters.

In order to evaluate the goodness-of-fit of the data with each probability distributions, we used the well-known Kullback–Leibler divergence (KL). Given a random sample $X_1, \ldots, X_n$ from a probability distribution $P(x)$ with density function $p(x)$ over a non-negative support. If we suppose that the sample comes from a specific probability distribution $Q(x)$ with a density function $q(x)$, the KL information on the divergence between $P(x)$ and $Q(x)$ is given by the following formula [28]:

$$D_{KL}(p\|q) = \int_0^{\infty} p(x) ln \frac{p(x)}{q(x)} dx. \tag{1}$$

It is known that the information divergence $D_{KL}(p\|q) \geq 0$. Therefore, if $D_{KL}(p\|q) = 0$, the sample comes from the specific probability distribution $Q(x)$ [29,30].

Therefore, we calculated the KL divergence between the proposed probability distributions and the wind speed data. We obtained the results shown in Fig. 3, which suggests that the GEV distribution fits the data better than the other two distributions.

Before applying the MFDFA, we decomposed the time series by using the Seasonal and Trend decomposition based on the Loess smoother (STL), proposed by Cleveland et al. [31]. In this method each wind speed time series is decomposed into trend (T_i), seasonal (S_i) and remainder (R_i) components.

The STL decomposition consists mainly of two important recursive procedures: an inner loop and an outer loop. The inner loop is used to update the trend and seasonal components, while the outer loop computes the robustness weights according to the remainder component, which will be used in the next iteration of the inner loop. The outer loop tends to reduce the weights of outliers or extreme values in the time series; in other words, the weights decrease by increasing the distance from x_i whereas the closest point to x_i has the largest weight.

In our study, the STL decomposition was implemented by using the *stl* function of the *"stats"* R library [32]. By setting the parameters: s.window = "periodic", inner = 1, outer = 15, s.degree = 1, and leaving the others as default in order that (1) each daily value of the seasonal component is calculated as the calendar mean (for instance, the value of the seasonal component at 1st January is the mean of the yearly values at 1st January of the time series; and (2) a robustness iteration for the inner and outer loops is guaranteed to better handle extreme values and outliers. For more theoritical details on the procedures of the STL decomposition, the reader can refer to Cleveland et al. [31].

Fig. 4 shows, as an example, the three components for the station Jungfraujoch: the seasonal (Fig 4(b)), the trend (Fig 4(c)), and the remainder (Fig 4(d)). As it can be clearly seen, the seasonal component is characterized by the annual oscillation, which is linked with the yearly meteo-climatic cycle. The trend component shows a slow time evolution of the wind speed, characterized by a very small range of variability. The remainder, instead, appears quite irregular and characterized by high frequency fluctuations, suggesting a "richer" dynamics that could be probably linked with the local topographic conditions of the measuring site. The apparent noisy character of the remainder component does not mean