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Temporal scale influence on multifractal properties of agro-meteorological time series

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ABSTRACT

Scale issues become very important when applying weather time series. We address problems associated with transferring meteorological data across time scales by comparing multifractal properties of hourly and daily meteorological time series. The multifractal detrended fluctuation approach revealed that temporal aggregation of agro-meteorological time series can impact on their multifractal properties. The most apparent evidence of changing the time scale on multifractal properties was found for precipitation. It was the least noticeable for the wind speed time series. The change from hourly to daily time scale had an effect on the long-range correlations and the broadness of the probability density function. The contribution of these two components to series multifractality was smaller than before data aggregation. Our results confirm the loss of unique multifractal features at daily time scale as compared to hourly time series.

1. Introduction

Long-term meteorological time series are the main source of information of the processes in the atmosphere related to climate change. They are used to analyze trends in specific periods, to simulate future predictions of climate and are inputs to crop production models (Schär et al., 2004; Moore et al., 2005; De Gooijer and Hyndman, 2006; Krug, 2007; Kahiluoto et al., 2014). Special interest in scale issues is evinced by modelling linkages across different temporal and/or spatial scales of a given process (Diaz-Nieto and Wilby, 2005; Wilby et al., 2014).

Many meteorological climate variables are considered in climate impact research, with air temperature and precipitation receiving the most attention. Other parameters receive much less attention, though they still may impact significantly on global functioning of ecosystems and on crop production. Frequently mentioned parameters linked to climate change processes are ozone concentration (Fagnano and Maggio, 2010), CO_2 concentration (Wang et al., 2016b), incident solar radiation and relative air humidity (Lohmann et al., 2006; King et al., 2015). The time scale of the series used in climate change studies is at least 30 years. However, other interesting aspects of time series analysis such as temporal and spatial scaling have successfully been performed on shorter time series (Derot et al., 2016). Scale issues can be dealt with by disaggregation and downscaling techniques. The downscaling approach aims at producing the finer-scale of the process with the required statistics being consistent with the process at the coarser scale. Disaggregation aims at producing a finer-scale process that adds up to the given coarse-scale total (Lombardo et al., 2012). Temporal scale problems are fundamental in prediction models, when the modelling scale is much smaller than that of the observation (Hoffmann et al., 2017). For instance, the scale discrepancy between model output and the resolution required for modelling was studied for hydrological models (Fowler et al., 2007; Groppelli et al., 2011), weather prediction models (Avila et al., 2015) and crop models (Pirttioja et al., 2015; Zhao et al., 2016; Ruiz-Ramos et al., 2017). Usually, long-term historical records from standard meteorological stations are delivered as daily data, but in many applications hourly or sub-hourly data are needed. This is similar to satellite meteorological data that are possessed at a temporal scale of several hours, while many applications require higher resolutions (Koutsoyiannis and Langousis, 2011). Therefore, the impact of temporal scale on the dynamics of complex systems are crucial and have attracted the attention of many authors (Chu et al., 1997; Stewart-Oaten and Bence, 2001; Hewitt et al., 2007; Zhou and Leung, 2010; Zhang and

Abbreviations: DFA, detrended fluctuation analysis; MFDFA, multifractal detrended fluctuation analysis; MFDMA, multifractal detrended moving average; WTMM, wavelet transform modulus maxima; STL, seasonal and trend decomposition using loess.

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Ge, 2013). Specifically, it is relevant to find out how the presence of localized trends and non-stationarities in the meteorological time series is preserved when changing their time scale. The non-stationarities of a time series can be evaluated via either their temporal fluctuations, which are expressed the presence of localized trends and non-stationarities in the meteorological time series is preserved when changing their time scale. The non-stationarities of a time series can be evaluated via either their temporal fluctuations, which are expressed through the power spectral density, or the long-range correlations in the series, i.e., correlations that decay as a power law shape of the power spectrum rather than the more intuitive exponential decay. Long-range temporal correlations indicate that even data points that are separated by a very long time still can be correlated.

Useful information about the dynamics of meteorological series and the impact of climate variability on ecological systems can be obtained by combining fractal and chaos methods for processing meteorological time series (Kalauzi et al., 2005; Chaudhuri, 2006). Various methodological approaches have been attempted in studying fractal phenomena in complex systems. These include Rescaled Range Analysis and Detrended Fluctuation Analysis – DFA, which are used to analyze properties of mono-fractal time series, as well as Multifractal Detrended Fluctuation Analysis – MFDFA (Kantelhardt et al., 2002), Multifractal Detrended Moving Average – MFDMA (Gu and Zhou, 2010) and Wavelet Transform Modulus Maxima –WTMM (Muzy et al., 1993), which are applied to study multifractal scaling and long-range correlation properties of non-stationary time series data. Many systems can be characterized by complex behavior, described as "multifractality" suggesting different scaling laws for different orders of correlations.

In particular, multifractal analysis is a powerful method to characterize long-range correlations within the time series through calculation of different scaling exponents for different parts of the series (Kantelhardt et al., 2006). Prior studies have indicated the multifractal nature of many meteorological quantities, including air temperature (Koscielny-Bunde et al., 1998; Bartos and Jánosi, 2006; Lin and Fu, 2008; Yuan et al., 2013), soil temperature (Jiang et al., 2013), precipitation (Deidda, 2000; García-Marín et al., 2008; De Lima and de Lima, 2009; Gemmer et al., 2011; Lovejoy et al., 2012), wind speed (Kavasseri and Nagarajan, 2005; Feng et al., 2009; Baranowski et al., 2015), and ozone concentration (Jimenez-Hornero et al., 2010), as time series of those quantities were shown to exhibit self-similar properties. Multifractals were introduced in the field of economics to surpass the shortcomings of classical theories that predict the impossibility of occurrence of precipitous events. When the dimension of a time series is noninteger, this is associated with two specific features: inhomogeneity – extreme fluctuations at irregular intervals, and scaling symmetries – definite relationships between fluctuations over different separation distances. In some cases, such as exchange rates, the underlying structural equations give rise to fractality. From among many methods of multifractal analysis, Multifractal Detrended Fluctuation Analysis (MFDFA) proved to be useful for studying multifractal scaling properties and the detection of long-range correlations in noisy, non-stationary time series (Kantelhardt et al., 2002). The application of this method confirmed multifractality of the majority of meteorological time series including rainfall (Valencia et al., 2010; Yu et al., 2014), ground surface temperature (Jiang et al., 2013), air temperature, and relative humidity (Baranowski et al., 2015).

The aim of this study is to elucidate to what extent the temporal aggregation of various meteorological time series influences their temporal scaling properties. For this purpose hourly and daily 14 years' time series of four different meteorological quantities are used.

2. Materials and methods

2.1. Study site and meteorological data

The experimental data were collected at a meteorological station located in Felin (51°15′N, 22°35′E), near Lublin, Poland. The area belongs to the Lublin Upland on the east bank of the Bystrzyca River, free of ravines, at an elevation of 205–215 m a.s.l., with the groundwater table at a depth of 15 m. The site has a warm summer continental climate (Köppen-Geiger climate classification: Dfb). The soil of the site is an Orthic Luvisol developed from loess over limestone. During the entire period of the experiment (i.e. 2001–2014), soil was covered with grass harvested five times a year, monthly from May to September. Long-term annual mean temperature and precipitation at the site are 8.9 °C and 564 mm, respectively.

The weather time series were measured from May 8th 2001 to November 11th 2014. Four variables were considered: air (2 m) and soil temperatures [°C], precipitation [mm] and wind speed [m s^{-1}]. All readings were recorded on a DL2e data logger (Delta-T Devices Ltd, U.K.). The air temperature was measured with an RHT2 sensor (Delta-T Devices Ltd, U.K.). It was mounted 2 m above the soil level, and each hourly reading was obtained as an average from 60 one-minute readings. The soil temperature was measured at a depth of 0.05 m in the soil profile with the waterproof IP68 sensor (Eijkelkamp, The Netherlands). This sensor is fitted with a Fenwall thermistor (2250 ohm at 25 °C) and has accuracy of 0.1 °C for the measuring range of 0–50 °C. Precipitation was measured 1 m above the grass cover with a rain gauge type RG2 (Delta-T Devices Ltd, U.K.). The wind speed was measured 2 m above the grass cover with an AN4 anemometer (Delta-T Devices Ltd, U.K.) every minute and was averaged to hourly values.

The descriptive statistics of the meteorological time series are presented in Table 1. The comparison of hourly and daily values of the studied meteorological time series reveals the high similarity of mean values and slight differences in maximum, minimum, standard deviation values, as should be expected, because those features should be smeared by time-averaging. The parameters of

Table 1
Descriptive statistics of the hourly and daily 14 years' meteorological time series from station located in Felin, Lubelskie Voivodship, Poland.

Meteorological variable	Time interval	Mean	Min	Max	Std	Median	Skewness	Kurtosis
Precipitation (mm)	hourly	0.1	0.0	51.0	0.48	0.0	27.675	1589.800
	daily	1.5	0.0	64.4	4.16	0.0	5.515	46.531
Wind speed (m/s)	hourly	1.6	0.0	20.2	1.11	1.4	1.293	7.048
	daily	1.6	0.0	6.7	0.83	1.4	1.338	5.515
Air temperature (°C)	hourly	8.9	−28.9	35.6	9.43	9.2	−0.139	2.596
	daily	8.9	−22.5	27.5	8.95	9.6	−0.328	2.433
Soil temperature (°C)	hourly	10.3	−5.4	47.4	8.46	10.1	0.190	1.789
	daily	10.3	−4.6	29.7	8.29	10.3	0.095	1.570

Mean, minimum, maximum, standard deviation (Std) and median have units corresponding to the units of meteorological variable; skewness and kurtosis are non-dimensional.