Theoretical and Applied Climatology (2019) 137:1811–1824
https://doi.org/10.1007/s00704-018-2705-0

ORIGINAL PAPER

Multifractal characterization and comparison of meteorological time series from two climatic zones

Jaromir Krzyszczak[1] · Piotr Baranowski[1] · Monika Zubik[1] · Valentin Kazandjiev[2] · Veska Georgieva[2] · Cezary Sławiński[1] · Krzysztof Siwek[3] · Jerzy Kozyra[4] · Anna Nieróbca[4]

Received: 22 July 2018 / Accepted: 2 November 2018 / Published online: 16 November 2018

Abstract

The results of the multifractal analysis performed for meteorological time series coming from four stations in Poland and Bulgaria located in varying climatic zones are presented. To assess climatic shift response (in 2001/2002), the analysis was conducted separately for two subsets. To analyze long-distance power-law correlations within the studied time series and evaluate the differences in dynamics of the climate between the analyzed sites and periods of time, the multifractal detrended fluctuation analysis methodology (MF-DFA) was proposed. It was revealed that the multifractal properties of precipitation differ considerably from other analyzed quantities. The singularity spectra were susceptible to climatic shift, what was indicated by the changes of spectra parameters. It was especially apparent for asymmetry, which changed from being right- to left-skewed, implying the occurrence of more extreme events. Similarities in the dynamics of meteorological processes for each of the climatic zones were proven by the close relation of respective multifractal spectra parameters coming from closely spatially related localizations.

1 Introduction

One of the major scientific challenges in climatology is to understand the basics of mechanisms leading to climate changes. Nowadays, quantification of the human role in change of climate is widely discussed, but what we perceive as climate change is an outcome of variations within meteorological time series that happen on timescales extending from interannual fluctuations even up to the age of the earth (Baker et al. 2007). Relying on what is currently known, climate has already shown in the history quite remarkable changes over different timescales. In particular, one of the most salient features of the past climate changes is the so-called 100-ky cycles observed in paleo-climatic records. According to Benzi (2010), these cycles were characterized by abrupt warming phases followed by tender declines of temperature. It is said that to understand a phenomenon basis, this phenomenon must be observed. However, if variability of some process occurs on a specific timescale t and a stochastic component is present in it, then to address those changes in a proper way, phenomenon must be observed over many intervals of t. Therefore, to understand, model, and predict climate change, meteorological time series from globally distributed points, being recorded over a long period of time, are required. Exploring temporal and spatial variability of those series is particularly important for assessing the type of climate system response to a variety of forcings. In numerous cases, the typically applied standard methods of analyzing temporal variability in climatic data are insufficient enough to elucidate changes in spatial patterns, which frequently stand for a variation of a climate in a local-scale. Hence, besides the typically used procedures basing on the quantification of trends and

Highlights
- Meteorological time series exhibit multifractality.
- Multifractality source for meteorological time series was evaluated.
- Spectra of precipitation differ from the other climate variables spectra.
- The singularity spectra were sensitive to climatic shift.
- Country-level similarity of the multifractal spectra parameters was observed.

✉ Jaromir Krzyszczak
jkrzyszczak@ipan.lublin.pl

[1] Institute of Agrophysics, Polish Academy of Sciences, ul. Doświadczalna 4, 20-290 Lublin, Poland

[2] National Institute of Meteorology and Hydrology, Bulgarian Academy of Sciences, 66 Tsarigradsko shausse, 1784 Sofia, Bulgaria

[3] Faculty of Earth Sciences and Spatial Management, UMCS, al. Kraśnicka 2cd, 20-718 Lublin, Poland

[4] Institute of Soil Science and Plant Cultivation, State Research Institute, Czartoryskich 8, 24-100 Pulawy, Poland

oscillations of the relevant meteorological quantities (Balling et al. 1998), more exquisite methods including fractal analysis and chaos theory are being established and successfully used to grasp the dynamics of processes occurring in the individual layers of the atmosphere (Higuchi 1988; Kalauzi et al. 2005). These novel approaches permit not only to derive trend and seasonality within the analyzed time series, but also to assess other features, such as the long-distance power-law correlations, what means that decay of those correlations takes place in accordance with the power law, instead as the more intuitive exponential decay. Such characteristics can be relevant and helpful for describing climate variability among specific regions and time periods at different scales. From among numerous methodologies that are used to successfully achieve this goal, multifractal analysis stands as a promising tool, as it gives information about not only long-distance power-law correlations, but also other inherent features of the time series. In this formalism, the generalized Hurst exponents are calculated, which refer to various scales within the series and are good measures of the self-similarity (Kantelhardt et al. 2006). The term "long-distance power-law correlation" or shorter—"long-range correlation", denotes the effect of memory within the structures of the series in temporal or spatial scales, causing a slow decrease of the correlation function that is accountable for a "non-local behavior" of the time series (Sánchez et al. 2005). This phenomenon, often referred as a "memory effect", can be described as influence of previous system states on the evolution of the system over time. "Multifractality" in this sense is connected to a complex behavior that can be spotted for some systems characterized by quantities, time series of which exhibit self-similar properties. This complex behavior is linked with different laws of scaling for various orders of correlations within analyzed time series. In other words, multifractality is an indication of the complex dynamics, for which a single exponent (like the fractal dimension) is not sufficient enough to fully characterize the phenomenon. The multifractal analysis as a section of the fractal theory was introduced on the ground of econometry (analysis of price fluctuations), being able to overpass the shortcomings of the classical theories in dealing with processes that undergo the scaling law. Also, two specific features can be linked with a time series when its dimension is non-integer—inhomogeneity, which means the occurrence of extreme fluctuations at irregular intervals, and scaling symmetries, which define relationships between fluctuations over different separation distances (Scarlat et al. 2007).

Over the course of past years, the multifractal features of many geo-physical processes and systems have become widely explored. As it has already been shown by Kantelhardt et al. (2006), MF-DFA can be applied to detect non-stationarities and overcoming trends in the noisy data at all timescales. It was confirmed that numerous processes in the soil-atmosphere system expressed through respective long time series exhibit multifractality, including wind speed (Kavasseri and Nagarajan 2005; Feng et al. 2009), relative air humidity (Baranowski et al. 2015), precipitation (de Lima and de Lima 2009; Gemmer et al. 2010; Valencia Delfa et al. 2010; Yonghe et al. 2013), temperature fluctuations of the oceanic waters (Fraedrich and Blender 2003), mean and extreme values of air temperature (Koscielny–Bunde et al. 1998; Bartos and Jánosi 2006; Yuan et al. 2012; Krzyszczak et al. 2017a), or temperatures of the soil in the soil profile (Jiang et al. 2013). Yu et al. (2014) applied multifractal formalism to investigate whether any relation between rainfall variability and the lay of land can be found.

There is good evidence of the multifractal structure of meteorological time series collected over a few years' period for single sites or small regions (Király and Jánosi 2005; García-Marín et al. 2008; Yonghe et al. 2013; Karatasou and Santamouris 2018). However, there is an increasing need to examine multifractal properties of long-term meteorological time series (at least 30 years) over large areas, belonging to the diverse climatic zones, in order to determine differences and variability in the climate dynamics. To find interactions between locally measured fluctuations and the fluctuations in larger scales, it is substantial to acknowledge the temporal scaling properties of the time series subjected to research. It was already indicated (Hoffmann et al. 2017; Krzyszczak et al. 2017b) that aggregation, whether in spatial or temporal scale, exceedingly impacts multifractal features of time series of agro-meteorological data. Therefore, data upscaling for research performed in a large scale should be done carefully and above effect, together with other issues, should be also considered. Also, in multi-ensemble crop growth and yield modeling (Pirttioja et al. 2015; Fronzek et al. 2018; Ruiz-Ramos et al. 2018) usually some alterations in the structure of the time series are being performed to include the effect of climate change, e.g., by shifting their amplitudes or oscillations. This procedure can modify inherent properties of time series, such as long-range correlations, and therefore they should be made very carefully.

The main idea of this work is to compare multifractal properties of chosen long-term meteorological time series recorded in two European countries in various climatic conditions, taking into account two climate shifts distinguished in recent decades: the first one around 1980, for which not only changes in the mean temperature were observed, but also the temperature variance changed in the periods before and after 1980 (Huntingford et al. 2013), and also before and after turn of the years 2001/2002 (Swanson and Tsonis 2009). The selected approach allows us to verify if changes in the dynamics of meteorological processes pointed out in the literature can be spotted with the use of the MF-DFA and try to generalize them for diverse climate conditions.

2 Materials and methods

2.1 Study sites and meteorological data

The multifractal analysis was performed using the time series of basic weather elements from the meteorological stations located in two European countries: Poland and Bulgaria, which vary with climatic conditions. The study was conducted for four stations: Lublin, Poland (51°15′ N, 22°34′ E, 170 m a.s.l.), Grabow, Poland (51°24′ N, 21°58′ E, 152 m a.s.l.), Knezha, Bulgaria (43°29′ N, 24°05′ E, 117 m a.s.l.), and Chirpan, Bulgaria (42° 12'N, 25° 19′E, 178 m a.s.l.). The Grabow and Lublin sites can be classified as having a warm summer continental climate (Köppen-Geiger climate classification: Dfb); however, the site in Lublin is within the city area, whereas the site in Grabow is situated among agricultural fields. According to the classification of climatic conditions within the Bulgarian territory (Sabev and Stanev 1959), Knezha is situated in the northern climatic region of the Danube plain within the moderate continental zone (Köppen-Geiger climate classification: Dfa). In this zone, summer is usually hot, whereas winter is cold and autumn is slightly warmer and drier than spring. The annual precipitation pattern has a continental character, with the maximum in June and the minimum in February (Kazandjiev 2011). Chirpan is located in the central-eastern Bulgarian climatic region belonging to the transitional continental climatic zone (Köppen-Geiger climate classification: Cfa). Hot summers and moderately cold winters (mild winters) can be usually observed in this zone. The annual precipitation pattern also has a continental character with the maximum during June and the minimum in February (Kazandjiev 2011). Both stations are situated in an area of agricultural fields. Weather data were collected from January 1, 1980, to December 31, 2010, using automatic weather stations with measuring sensors of similar sensitivity and accuracy for all sites. All the measurements were performed in compliance with WMO standard. The time series of 11,323 daily observations of the following four variables were considered in the present study: air temperature (°C), precipitation (mm), relative air humidity (%), and wind speed (m s^{-1}). In an effort to ascertain the climate shifts indicated in the literature, the analyzed time series were split into two subsets. One subset contained data from the 1980–2001 period (8036 records), whereas the second one from the 2002–2010 period (3287 records). The descriptive statistics of the used subsets of time series from all the study sites are presented in Table 1.

The highest mean and median values of air temperature were observed at the Chirpan station, whereas the lowest ones for the Grabow station for both sub-periods. The Grabow station is also characterized by the lowest values of minimum and maximum temperatures and the highest values of mean and median relative air humidity and wind speed, also for both sub-periods. Generally, the sites in Poland show lower values of temperature (mean, min., max., and median) and slightly higher values of relative air humidity and wind speed than the sites in Bulgaria for both sub-periods. Also, higher values of air temperature for the second sub-period can be observed for all the stations (mean, min., max., and median), thus indeed indicating the shift in temperature reported around 2001/2002. For the wind speed time series, the mean values are similar for both sub-periods and for all the stations, while the maximum observed values are lower in the second sub-period and some change in medians can be observed, which suggests that the structure of the wind speed time series changed in the second sub-period, becoming more regular and less dominated by extreme (maximal) values.

2.2 Seasonal detrending

Before performing fractal analysis, it is important to filter out the periodicities that occur in the data structure, as it was already shown that they influence non-linear properties of the time series (Livina et al. 2011). A method of periodicities substraction that was applied in our study is called the STL (Seasonal and Trend decomposition using Loess). This method is based on repeatedly applied smoothing procedures that use the locally weighted regression, or loess (Cleveland et al. 1990). After decomposing time series into seasonality, trend, and remainder, the STL procedure removes seasonality and the remaining components are added together to produce a "new" time series. The usefulness of the STL formalism for preparing the data series in advance to the application of the MF-DFA method was confirmed by Li et al. (2015).

2.3 MF-DFA analysis

After the seasonal detrending, acquired time series of meteorological elements were subjected to the Multifractal Detrended Fluctuation Analysis to uncover their scaling characteristics. MF-DFA formalism makes it possible to unfold the scaling behavior of the fluctuations in the time series and to find the spectrum of singularities. The MF-DFA scheme, which was proposed in 2002, generalizes the formalism of Detrended Fluctuation Analysis and was formulated and spread by Kantelhardt et al. (2002). It expands DFA applicability and enables studies on the multifractal nature of the time series of quantities describing miscellaneous processes (Peng et al. 1994). The procedure of performing multifractal analysis relies on five steps performed for each of the data series X_i of length N (Kantelhardt et al. 2002):

(1) The "profile" $Y(i)$ is created by converting the noises into random walks:

$$Y(i) = \sum_{i=1}^{k} [X_i - \langle X \rangle], \qquad k = 1, \ldots, N \tag{1}$$

Table 1 Descriptive statistics of the analyzed subsets of the meteorological time series from the stations in Bulgaria (Chirpan, Knezha) and Poland (Grabow, Lublin)

Variable	Location	Mean	Min.	Max.	SD	Median	Mean	Min.	Max.	SD	Median
		1980–2001					2002–2010				
Relative air humidity (%)	Chirpan	73.67	33	100	13.96	74.0	72.70	38.0	100	13.48	72
	Knezha	72.71	28	100	13.14	72.0	70.52	38.0	98	12.36	70
	Grabow	79.04	33	100	11.57	80.5	78.58	32.0	100	13.43	81
	Lublin	77.26	29	100	11.78	76.3	74.99	31.7	100	13.27	76.3
Air temperature (°C)	Chirpan	11.94	− 17.8	32.3	9.18	12.4	12.40	− 14.3	33.6	9.08	12.9
	Knezha	10.93	− 22.6	34.0	9.67	11.8	11.45	− 21.7	34.8	9.65	12.2
	Grabow	7.92	− 26.6	27.6	8.58	8.4	8.54	− 25.2	27.2	8.92	9.0
	Lublin	8.42	− 22.8	28.1	8.74	8.9	9.24	− 21.3	28.3	9.04	9.8
Precipitation (mm)	Chirpan	1.36	0	56.7	4.41	0	1.63	0	73.0	5.36	0
	Knezha	1.43	0	80.0	4.36	0	1.66	0	59.8	4.88	0
	Grabow	1.72	0	64.0	4.53	0	1.74	0	105.9	4.68	0
	Lublin	1.46	0	61.6	4.02	0	1.49	0	47.6	3.83	0
Wind speed (m s^{-1})	Chirpan	2.05	0	16.3	1.89	1.7	1.93	0	10.0	1.65	1.3
	Knezha	2.20	0	32.0	2.42	0	2.10	0	13.0	1.78	1.7
	Grabow	3.82	0	21.0	1.88	3.6	3.60	0	14.0	1.59	3.3
	Lublin	2.59	0	10.3	1.26	2.3	2.68	0	8.7	1.13	2.7

(2) The procedure of dividing the "profile" into $N_s = int(N/s)$ non-overlapping slices of the same length s is redone from two opposite ends of the series because the lengths s and N of the series are disproportionate numbers and a short part at the end of the profile may remain after each division. As a result, $2N_s$ segments are obtained in total.

(3) Trends for all of the $2N_s$ segments are determined to calculate the variance:

$$F^2(s,v) = \frac{1}{s}\sum_{i=1}^{s}\{Y[(v-1)s+i]-y_v(i)\}^2, \qquad v = 1,\ldots,N_s \quad (2)$$

$$F^2(s,v) = \frac{1}{s}\sum_{i=1}^{s}\{Y[N-(v-N_s)s+i]-y_v(i)\}^2, \quad v = N_s+1,\ldots,2N_s \quad (3)$$

where $y_\nu(i)$ is the trend function in segment ν.

(4) The generalized q-th order fluctuation function $F_q(s)$ is calculated:

$$F_q(s) = \left\{\frac{1}{2N_s}\sum_{v=1}^{2N_s}\left[F^2(s,v)\right]^{q/2}\right\}^{1/q}. \quad (4)$$

(5) It is checked if $F_q(s)$ obeys the power-law behavior for the large values of s, according to the formula:

$$F_q(s) \sim s^{h(q)}, \quad (5)$$

where $h(q)$ means the generalized Hurst exponent. After using the equation $\tau(q) = qh(q) - 1$ and the Legendre transformation $\alpha = \frac{d\tau}{dq}$, the multifractal spectrum is obtained as:

$$f(\alpha) = q\alpha - \tau(q). \quad (6)$$

Figure 1 presents a schematic singularity spectrum with indications of all of the important parameters: α_{max}, α_{min}, α_0, a_s, and w. According to Mali (2014), the width of the spectrum w (the difference between α_{max} and α_{min}) can be regarded as a direct measure of the degree or complexity of multifractality. It shows the length to which the fractal exponent extent in the series, being an indicator of the "richness" of the signal structure. The greater is the value of w, the more developed is the multifractality. On the contrary, for pure monofractal, the width w of the spectra equals to 0, but, according to Makowiec and Fuliński (2010), if it is lesser than

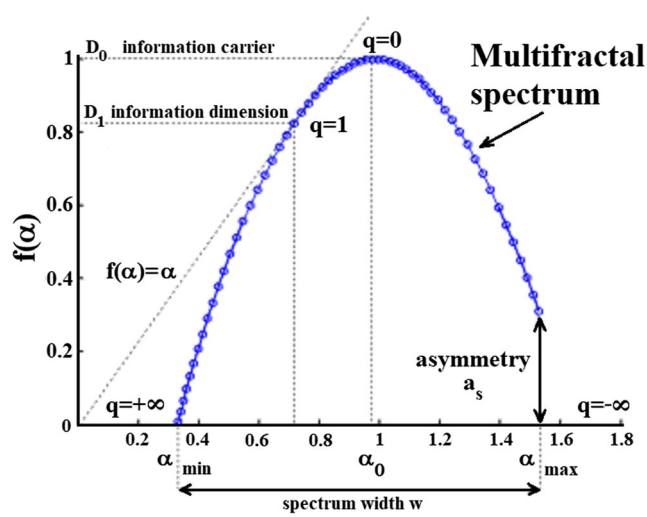

Fig. 1 Schematic presentation of the main parameters of a multifractal spectrum

0.05, then monofractal behavior of the spectrum should be assumed. The type of events in the studied process is indicated by α parameters. The α_{min} parameter indicates the most extreme and α_{max} the smoothest events in the studied process. The α_0 parameter delivers valuable information about the structure of the studied process, with a high value indicating that it is less correlated and possesses fine structure. If the underlying process becomes correlated and loses its fine structure, becoming more regular in appearance, the α_0 value, which indicates at which value of α multifractal spectra achieves its maximum, is low. The multifractal spectrum shape is strongly modified by the asymmetry parameter a_s. The negative values of the a_s (shape of the singularity spectra is left-skewed) indicates low fractal exponents of small weights, which imply that the extreme events play a prominent role in the temporal structure of the time series (Telesca and Lovallo 2011). In contrast, a right-skewed spectrum (positive value of a_s) means fairly strong weighted fractal exponents, which are typical in fine structure series. Therefore, the values of the multifractal spectrum parameters (α_0, w, a_s) can be used as quantitative and qualitative indicators of the dynamics of the meteorological processes.

In general, two separate sources of the time series multifractality can be distinguished. As described by Kantelhardt et al. (2002), they are as follows: a broad probability distribution (PDF) of the data or long-range (time) correlations of the small and large fluctuations. Of course, multifractality can be driven either by one of the sources or simultaneously by both of them (Min et al. 2013; Mali 2014). To check which source of multifractality is dominant for a given time series, the tests with the utilization of randomly shuffled data (which remove any long-range temporal correlations) and surrogate data (if the surrogated data spectra display no multifractality, a PDF is mostly responsible) were performed. If, by shuffled data test, the obtained singularity spectra exhibit non-multifractal properties, then multifractality is only caused by long-distance power-law correlations. On the contrary, if the shuffled series display diminished multifractality compared to the undistorted series (that is the spectra widths decrease), then long-range correlations play the main role in the multifractality of the data, but each of the two kinds of multifractality may be present in the analyzed time series. It is because the shuffling operation (random change of arrangement of the data) does not affect statistical distribution of the data, and therefore no alterations in spectra shape should be visible. To check to what extent the broad probability distributions influence the multifractality of the series, surrogates were created utilizing the formalism described by Theiler et al. (1992) and which is usually titled as Amplitude Adjusted Fourier Transform. The range of s value for calculation of the fluctuation function $F_q(s)$ was set as 10 up to 300 events as a result of several trials and maintaining the highest possible stability of the obtained spectra as a criterion of selection.

To prevent a potential distortion of the results by the so-called "freezing" phenomenon (Kantelhardt et al. 2006), the range of q had to be narrowed to [− 5;5]. This was because the density distributions of all the studied meteorological time series had heavy tails, which means that their tails were not exponentially bounded.

3 Results and discussion

The fluctuation functions $F_q(s)$ versus s were calculated for the 1980–2001 and 2002–2010 periods for all the studied meteorological quantities and presented as log-log plots (Fig. 2) to assess their scaling behavior. The quality of fit of the regression lines indicates whether the relationship can be considered as scale invariant. If a linear approximation dependence is detected over the same range of scales and the Pearson correlation error R^2 is higher than 0.98, then the scaling exponents $\tau(q)$ are considered as representative for the underlying scaling phenomenon (Makowiec and Fuliński 2010). In our case, relationships between $\log(F_q(s))$ and $\log(s)$ can be represented by straight (not curved or S-shaped) lines for any of the analyzed time series, with very high (0.98–0.999) coefficients of determination R^2, disregardless of the timescale. Therefore, it can be presumed that the decomposed time series used in the presented study are scale invariant and meet the requirements of further analysis. However, it may be noticed that the straight, unbent lines representing changes of $F_q(s)$ vs s have slopes ranging from 0.53 to 0.84, which reveals that the scaling behavior of the analyzed variables, locations, and periods differ considerably. It is especially obvious when comparing the slopes of the relative air humidity and air temperature fluctuation functions for all the analyzed stations and periods (H~0.7–0.8) with the slopes of the precipitation and wind speed fluctuation functions (H~0.55–0.60). Also, some differentiation between sub-periods (especially visible for relative air humidity and air temperature) and between stations in Poland and Bulgaria (particularly evident for the first sub-period of relative air humidity and the second sub-period of air temperature) can be noticed. In conclusion, it can be stated that climatic conditions and climatic shifts have some impact on fluctuations present in the time series, as the slopes of fluctuation functions $F_q(s)$ of time series of meteorological elements are influenced by them.

To give the possibility of checking the origin of multifractality of the time series, surrogates and shuffled series were generated. Multifractal spectra of relative air humidity (Fig. 3), air temperature (Fig. 4), precipitation (Fig. 5), and wind speed (Fig. 6) for the original, shuffled, and surrogate time series were analyzed for all locations and both sub-periods. The respective multifractal parameters of the spectra are provided in Table 2 for the 1980–2001 period and in Table 3 for the 2002–2010 period.

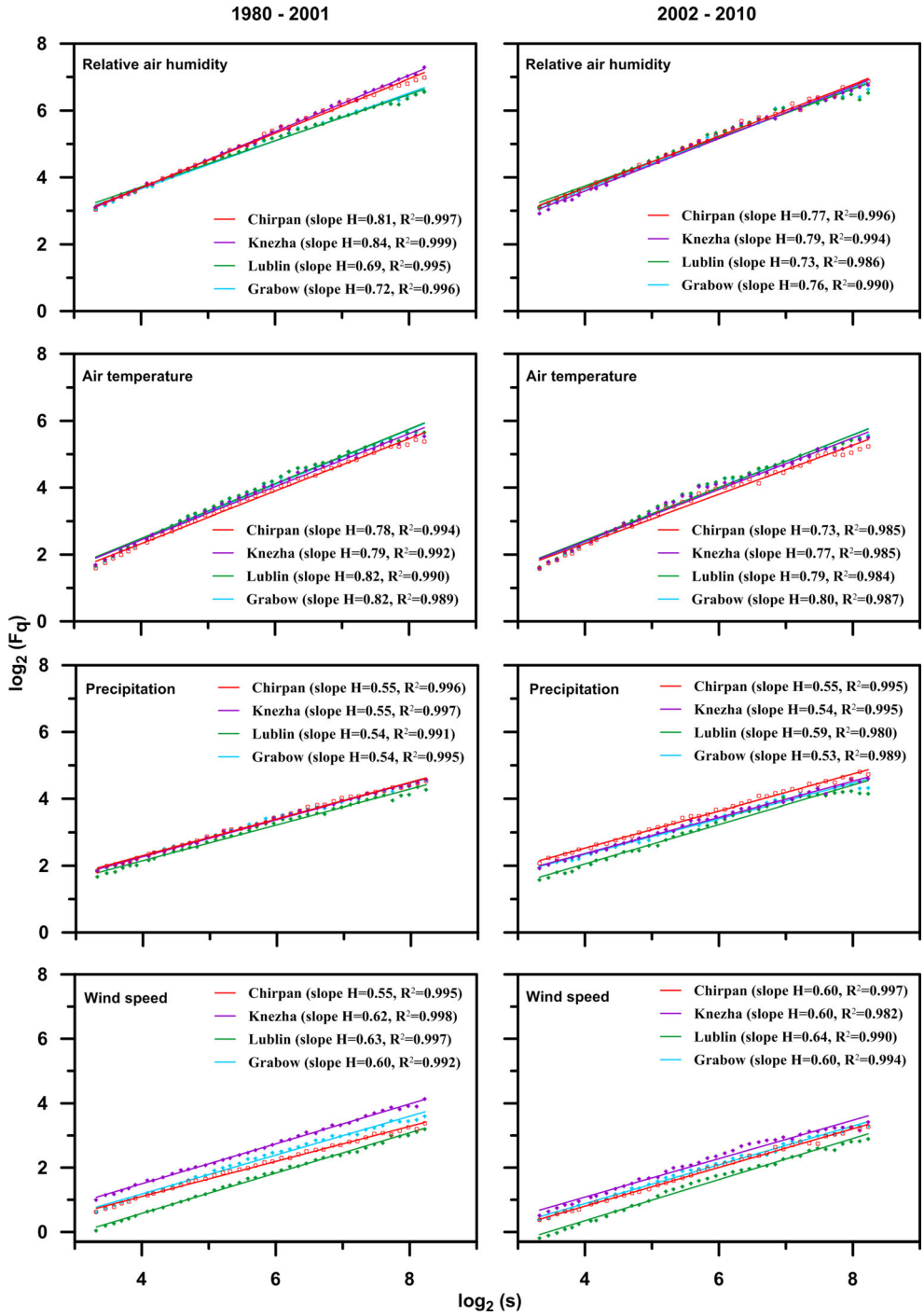

Fig. 2 The log-log plots of the fluctuation function $F_q(s)$ versus timescale s calculated for four meteorological time series (relative air humidity—first row; air temperature—second row; precipitation—third row; wind speed—last row) divided into two periods: 1980–2001 period (left column) and 2002–2010 period (right column)

The presented spectra with their multifractal parameters are proof that all the analyzed time series exhibit multifractal properties for both sub-periods and at all the locations, as the width w parameter of the original time series is higher than 0.05. Also, the spectra of the precipitation time series seem to be different from the spectra of the other time series, as w is two or even three times larger. After the shuffling procedure, the multifractal spectra become considerably narrower—even two or three times—for all the meteorological quantities, locations, and sub-periods, except for precipitation, for which the spectrum narrows by several percent. The huge narrowing of the shuffled spectra suggests that long-range correlations play the main role in the multifractality of the relative air humidity, air temperature and, to a lesser degree, wind speed time series, whereas the narrowing of the spectra of precipitation by several percent suggests that long-range correlations may be an important, but not the main, source of multifractality of those time series. We also observe some changes in the multifractal spectra pattern of

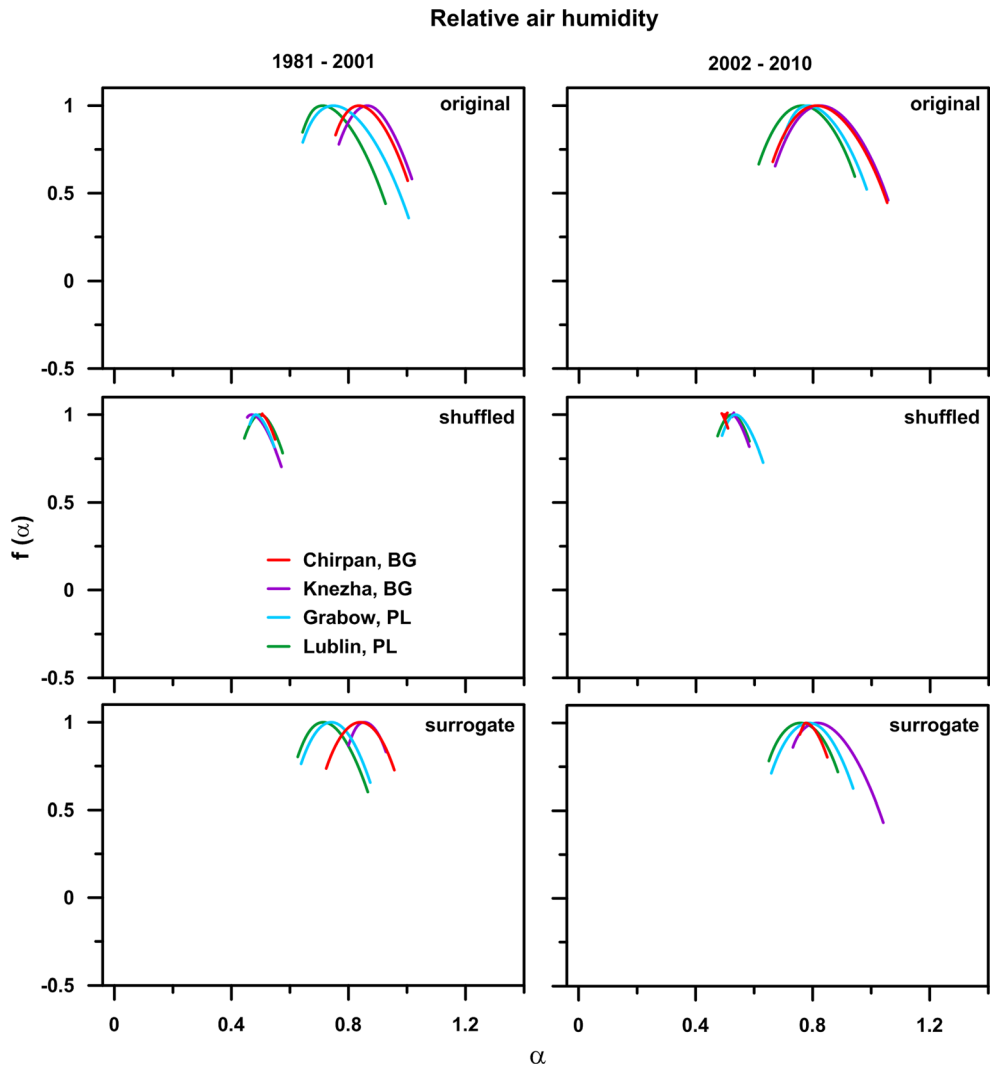

Fig. 3 Multifractal spectra of relative air humidity time series recorded at the stations located in Poland (Lublin and Grabow) and Bulgaria (Knezha, Chirpan), plotted for the 1980–2001 (left column) and the 2002–2010 (right column) subsets. Subsequent rows show the original (upper), shuffled (middle), and surrogate data (bottom row). $f(\alpha)$ is the singularity spectrum and α is the singularity strength

the relative air humidity, air temperature, and wind speed surrogate data compared to the corresponding spectra of the original data, but those changes do not seem to be vast. Therefore, it can be concluded that the broadness of the PDF impacts the multifractality of those time series only slightly and mainly the long-distance power-law correlations evoke multifractality. Notwithstanding, for the precipitation time series, the change in shape of the surrogate spectra is more evident. It should therefore be assumed that the broadness of the PDF affects more substantial the multifractality of those time series.

To validate if the abovementioned characteristics are indeed intrinsic and apparent in the data, the absolute differences of the Hurst exponents for the original and shuffled data $|h(q) - h_{shuf}(q)| = |h_{cor}(q)|$ and the original and surrogate data $|h(q) - h_{sur}(q)| = |h_{PDF}(q)|$ for the $q \in [-5;5]$ were calculated (Fig. 7). Hurst exponents characterize the power-law pattern of large and small fluctuations for positive and negative q values, respectively. The more the shuffled (surrogate) spectra diverge from the spectra of the original data, the absolute differences of the Hurst exponents attain higher values. And with higher values of the absolute differences of the Hurst exponents, the contribution of the long-distance power-law correlations (when considering shuffled vs original spectra) or the broadness of the PDF (surrogate vs original) to multifractality is greater. And indeed, for relative air humidity and air temperature for the whole range of q, we observed that disregardless of the analyzed subset or location, multifractality from long-range correlations is dominant, whereas the broadness of the PDF plays a very minor role in multifractality of these quantities. Likewise, for the wind speed time series, the long-range correlations have a greater influence on multifractality than the broadness of PDF (except for the Chirpan station in the first sub-period for $q > 3.5$), but they are not so dominant as for relative air humidity and air temperature. On the contrary, for the precipitation time series, the broadness of the PDF is at least as important for multifractality as the long-range correlations, since either the corresponding absolute differences of the Hurst exponents is alternately greater, depending on the q value (as for most of the cases), or their contribution to multifractality is basically on the same level for the entire range of q (as it is for

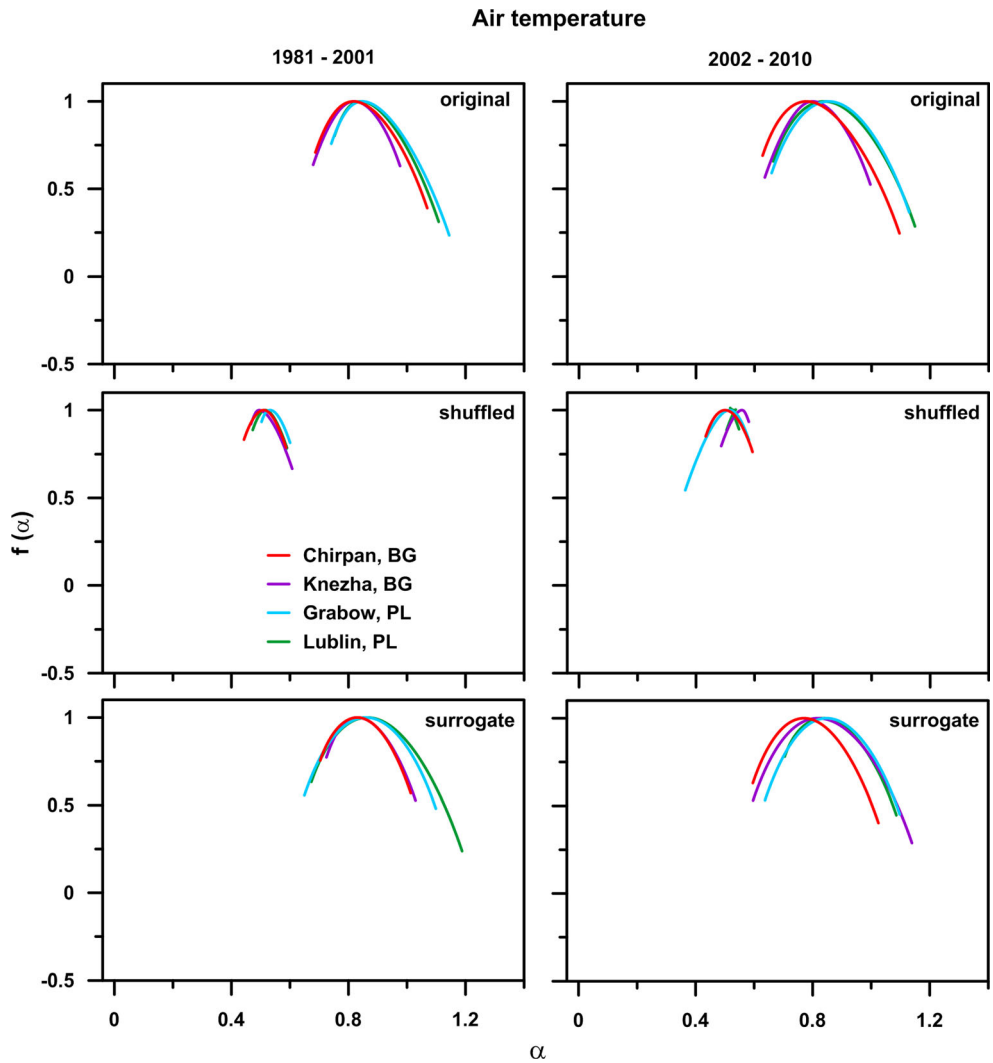

Fig. 4 Multifractal spectra of air temperature time series recorded at the stations located in Poland (Lublin and Grabow) and Bulgaria (Knezha, Chirpan), plotted for the 1980–2001 (left column) and the 2002–2010 (right column) subsets. Subsequent rows show the original (upper), shuffled (middle), and surrogate data (bottom row)

Chirpan station, second sub-period). It is clearly seen from the obtained results that the multifractal spectrum of the precipitation time series differs considerably from the spectra of other climatic variables analyzed. The predicted effect of the impact of climate change on precipitation is that the spatial and temporal patterns of this quantity are subject to vast changes, thus significantly influencing their PDFs. As the multifractality of precipitation results not only from the long-distance power-law correlations, but also from the broad probability density function, thus precipitation, from among the other studied climate variables, is more susceptible to changes of climate dynamics. This makes precipitation, which is currently difficult to forecast, even more unpredictable in the context of future climate changes. This outcome is coherent with the results presented in other papers (Baranowski et al. 2015; Krzyszczak et al. 2017b).

The comparison of the parameters of the multifractal spectra between the stations in Bulgaria and Poland indicates that for nearly all analyzed meteorological elements considerable differentiation can be spotted. Firstly, the close relation between the values of the maximum α_0 in relative air humidity and air temperature in both sub-periods, and in precipitation for the first (1980–2001) sub-period, could be observed for stations belonging to the same climatic zone. But in the case of precipitation, α_0 for the stations located in Bulgaria is only slightly larger compared to the stations in Poland (~ 0.76 vs ~ 0.74), which means that the underlying processes are slightly less correlated and have a slightly finer structure, whereas for relative air humidity and air temperature, these differences are more visible (from ~ 4% for air temperature in the first sub-period, up to ~ 15% for relative air humidity in the first sub-period). It is interesting that whereas for relative air humidity, the stations located in Bulgaria have larger α_0 values than the stations in Poland (~ 0.85 vs ~ 0.74 in the first sub-period and ~ 0.82 vs ~ 0.77 in the second sub-period), for air temperature, it is the opposite (~ 0.82 vs ~ 0.85 in the first sub-period and ~ 0.79 vs ~ 0.85 in the second sub-period), which means that in Poland, the underlying processes governing the relative air humidity dynamics are more correlated and have a less fine structure (a structure more regular in appearance) compared to the processes governing the relative air humidity dynamics in

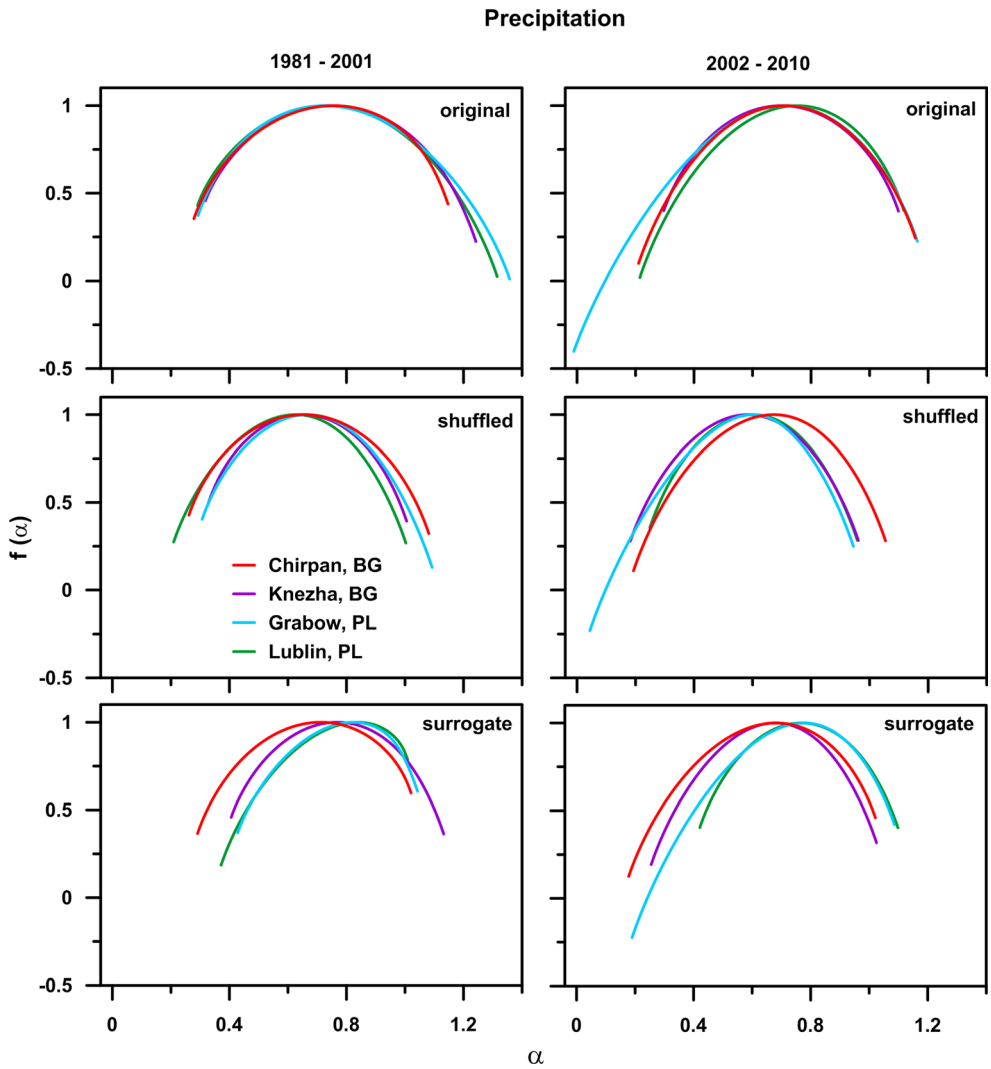

Fig. 5 Multifractal spectra of precipitation time series recorded at the stations located in Poland (Lublin and Grabow) and Bulgaria (Knezha, Chirpan), plotted for the 1980–2001 (left column) and the 2002–2010 (right column) subsets. Subsequent rows show the original (upper), shuffled (middle), and surrogate data (bottom row)

Bulgaria, whereas for air temperature, it is contrary and those differences are a slightly less noticeable. Secondly, the same close relation can be observed for the width of the spectrum w in both sub-periods of the relative air humidity, precipitation first (1980–2001) and second (2001–2010) sub-period of wind speed series. In case of the wind speed second sub-period, the Bulgarian stations have more homogeneous values of the spectrum width than the stations located in Poland, for which w differs not only from the Bulgarian stations, but also among themselves. The lowest value of the width of the spectrum in both sub-periods was observed for the Lublin station. As w parameter is connected to the "richness" of the signal structure, obtained result may be related to the fact that this station, contrary to the others, is located within the city area. Such a location may "promote" some values of the wind speed, while in turn neglecting other values and making the signal structure less rich. It is interesting that for relative air humidity, the multifractality is more developed for the Polish stations in the first sub-period (larger values of w), whereas in the second sub-period, it is inverse, i.e., the Bulgarian stations are characterized by a "richer" signal structure. In the other analyzed cases, the local climate characteristics manifest themselves more strongly than the regional ones, as either no close relation of the multifractal spectra parameters can be observed (as in the first air temperature sub-period) or the multifractal spectra widths of meteorological quantities coming from one station are completely different than these of the others (as in the first wind speed sub-period and the second air temperature sub-period for the Knezha station or the second precipitation sub-period for the Grabow station). Similar country-level congruence can also be observed for the asymmetry parameter a_s for the first sub-period of relative air humidity and air temperature as well as for both sub-periods of precipitation, especially for the Polish stations. It is interesting that generally, the spectra are rather right-skewed (which suggests that fine structures are more frequent) or tend to be symmetrical in shape. However, the extreme events become dominant for the second sub-period of precipitation, as the spectrum of the respective time series is left-skewed.

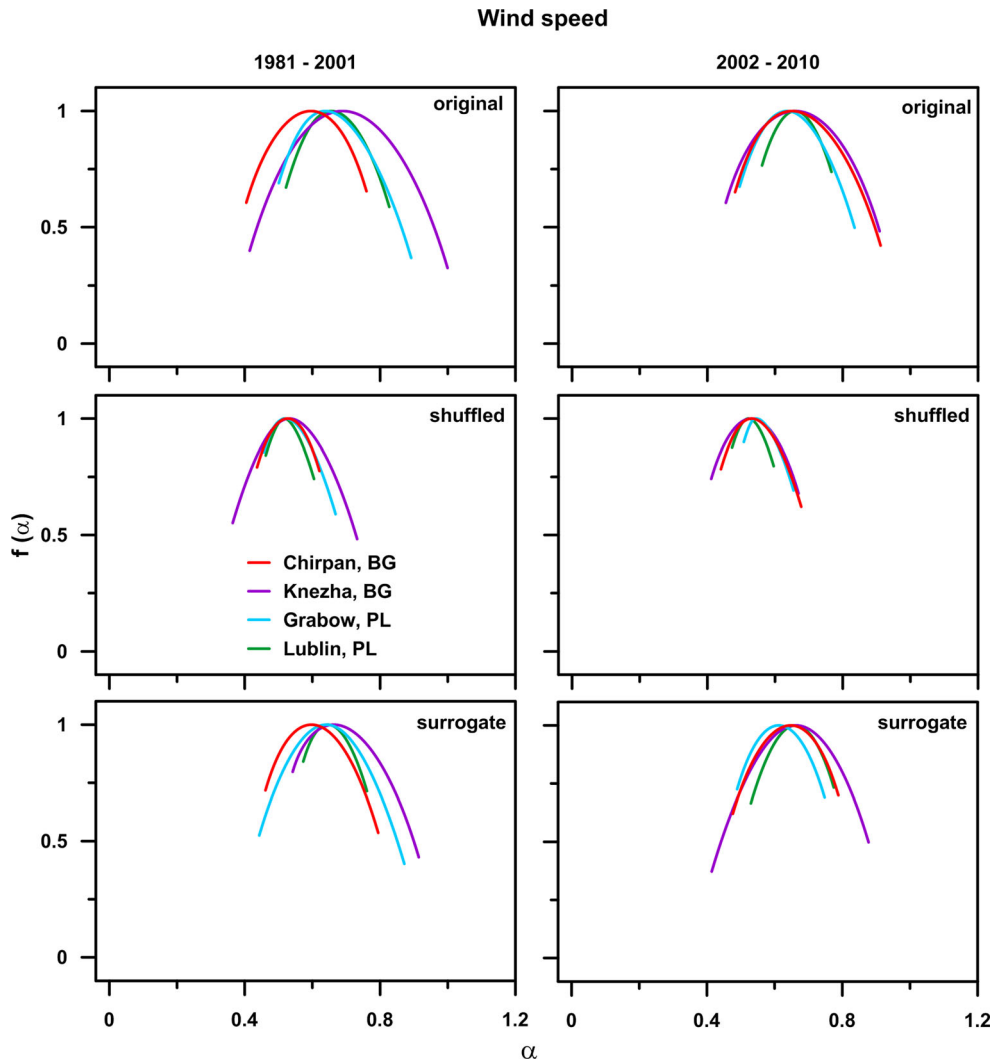

Fig. 6 Multifractal spectra of wind speed time series recorded at the stations located in Poland (Lublin and Grabow) and Bulgaria (Knezha, Chirpan), plotted for the 1980–2001 (left column) and the 2002–2010 (right column) subsets. Subsequent rows show the original (upper), shuffled (middle), and surrogate data (bottom row)

Another aspect that is interesting to address is a comparison of the parameters of the multifractal spectra between the two sub-periods, namely 1980–2001 and 2002–2010. It allows us to address the question whether the MF-DFA method can be applied as an indicator of the changes in the dynamics of atmospheric processes before and after the observed climatic shift. It can be discovered that the values of α_0 change only slightly and are greater in the second sub-period for the relative air humidity and air temperature recorded at the Polish stations, for the precipitation at the Lublin site and the wind speed at the Chirpan and Lublin sites, whereas they are lower for the relative air humidity, air temperature and precipitation recorded at the Bulgarian stations, the precipitation at the Grabow site, and the wind speed at the Knezha and Grabow sites. Those variations are usually smaller than the changes between regions with differing climate conditions. Contrastingly, w changes more vastly. The multifractality is more developed in the second sub-period for: (i) air temperature by about 20% in case of the Bulgarian stations and the station in Grabow, and about 40% in case of Lublin station; (ii) relative air humidity by about 60% for the Bulgarian stations and about 15% for the station located in Lublin; (iii) precipitation recorded at Chirpan and Grabow by about 10%; and (iv) wind speed recorded at the station in Chirpan by about 20%. In turn, a decrease in the length of the range of fractal exponents in the signal was observed in the second sub-period for: (i) wind speed by about 20% for Knezha and Grabow and 30% for the Lublin station; (ii) precipitation recorded at Knezha and Lublin by about 10%; (iii) relative air humidity by about 20% for the Grabow station. In the case of the asymmetry, more consistent changes can be observed, as in the second sub-period, this parameter is generally lower or even changes its sign to negative (either the spectrum tends to be more symmetrical or the asymmetry changes from right to left-skewed), which means that more extreme events can be observed for this sub-period, or even (in case of left-skewed precipitation) a predominance of extreme events in spectrum is present. Only the wind speed and air temperature time series recorded at the Bulgarian stations break out of this trend, as the asymmetry for those time series is slightly more positive. Some differences between both sub-periods can be also seen when

Table 2 Parameters of MF-DFA spectra of meteorological parameters from the stations in Bulgaria (Chirpan, Knezha) and Poland (Grabow, Lublin) for years 1980–2001

Variable	Location	a_s Original	w	α_0	a_s Shuffled	w	α_0	a_s Surrogate	w	α_0
Relative air humidity (%)	Chirpan	0.2607	0.2466	0.8371	0.1370	0.0459	0.5056	0.0092	0.2329	0.8420
	Knezha	0.1982	0.2497	0.8658	0.2822	0.1162	0.4700	0.0373	0.1281	0.8552
	Grabow	0.4323	0.3619	0.7504	0.1286	0.0840	0.4836	0.1070	0.2364	0.7425
	Lublin	0.4081	0.2836	0.7130	0.0825	0.1310	0.4986	0.2006	0.2396	0.7149
Air temperature (°C)	Chirpan	0.3179	0.3821	0.8189	0.0448	0.1440	0.5110	0.1859	0.3095	0.8322
	Knezha	0.0067	0.2968	0.8215	0.2531	0.1409	0.4962	0.2458	0.3045	0.8327
	Grabow	0.5236	0.4030	0.8494	0.1197	0.0976	0.5326	0.0747	0.4492	0.8623
	Lublin	0.4902	0.3561	0.8432	0.1035	0.1173	0.5169	0.3945	0.5150	0.8676
Precipitation (mm)	Chirpan	−0.0844	0.8684	0.7682	0.1061	0.8198	0.6630	−0.2300	0.7296	0.7213
	Knezha	0.2328	0.9242	0.7617	0.1024	0.6776	0.6584	0.0949	0.7261	0.7763
	Grabow	0.3615	1.0646	0.7353	0.2743	0.7861	0.6740	−0.2359	0.6146	0.8295
	Lublin	0.4036	1.0239	0.7409	0.0061	0.7935	0.6324	−0.5993	0.6378	0.8447
Wind speed (m s^{-1})	Chirpan	−0.0490	0.3552	0.5981	0.0155	0.1844	0.5279	0.1819	0.3333	0.5994
	Knezha	0.0742	0.5848	0.6930	0.0689	0.3678	0.5339	0.3663	0.3726	0.6660
	Grabow	0.3221	0.3913	0.6400	0.2655	0.2123	0.5217	0.1222	0.4287	0.6430
	Lublin	0.0833	0.3053	0.6577	0.1009	0.1426	0.5177	0.1269	0.1883	0.6470

analyzing the absolute differences of Hurst exponents for the original and shuffled data or original and surrogates (Fig. 7). Even though we do not see a change between both sub-periods regarding which source of multifractality is dominant, the contribution of long-range correlations and the broadness of the PDF slightly change. We can notice that (i) for relative air humidity recorded at the Chirpan station, both contributions to the multifractality source are larger in the second sub-period, (ii) for air temperature at the Polish stations, the contribution of long-range correlations increases, whereas that of the broadness of the PDF slightly decreases in the second sub-period, and for the Knezha station the contribution of the broadness of probability density function increases, and (iii) for wind speed at Chirpan, both sources have larger contributions to multifractality in the

Table 3 Parameters of MF-DFA spectra of meteorological parameters from the stations in Bulgaria (Chirpan, Knezha) and Poland (Grabow, Lublin) for years 2002–2010

Variable	Location	a_s Original	w	α_0	a_s Shuffled	w	α_0	a_s Surrogate	w	α_0
Relative air humidity (%)	Chirpan	0.2336	0.3910	0.8142	0.0590	0.0090	0.5072	0.1305	0.0936	0.7774
	Knezha	0.1951	0.3861	0.8269	0.1702	0.0581	0.5291	0.4283	0.3089	0.8177
	Grabow	0.2933	0.2849	0.7848	0.1526	0.1404	0.5355	0.0867	0.2797	0.7887
	Lublin	0.0705	0.3283	0.7652	0.0300	0.1087	0.5234	0.0629	0.2358	0.7599
Air temperature (°C)	Chirpan	0.4442	0.4677	0.7802	0.0874	0.1599	0.5001	0.2269	0.4292	0.7729
	Knezha	0.0403	0.3605	0.8004	−0.1385	0.0942	0.5568	0.2427	0.5427	0.8213
	Grabow	0.2242	0.4701	0.8556	−0.2841	0.2176	0.5150	0.0801	0.4602	0.8506
	Lublin	0.3714	0.4843	0.8404	−0.0053	0.0424	0.5168	0.3337	0.3816	0.8374
Precipitation (mm)	Chirpan	−0.1450	0.9460	0.7180	−0.1713	0.8615	0.6793	−0.3344	0.8432	0.6899
	Knezha	0.0032	0.8017	0.7080	−0.0035	0.7790	0.5900	−0.1245	0.7702	0.6847
	Grabow	−0.6273	1.1740	0.7211	−0.4801	0.9005	0.6050	−0.6455	0.8967	0.7827
	Lublin	−0.3811	0.9032	0.7606	0.0721	0.7092	0.6073	0.0012	0.6772	0.7741
Wind speed (m s^{-1})	Chirpan	0.2299	0.4300	0.6528	0.1615	0.2374	0.5321	−0.0787	0.3119	0.6496
	Knezha	0.1222	0.4545	0.6630	0.0625	0.2580	0.5317	−0.1258	0.4636	0.6653
	Grabow	0.1767	0.3399	0.6367	0.2078	0.1470	0.5457	0.0354	0.2586	0.6140
	Lublin	0.0278	0.2051	0.6603	0.0786	0.1231	0.5226	−0.0676	0.2450	0.6628

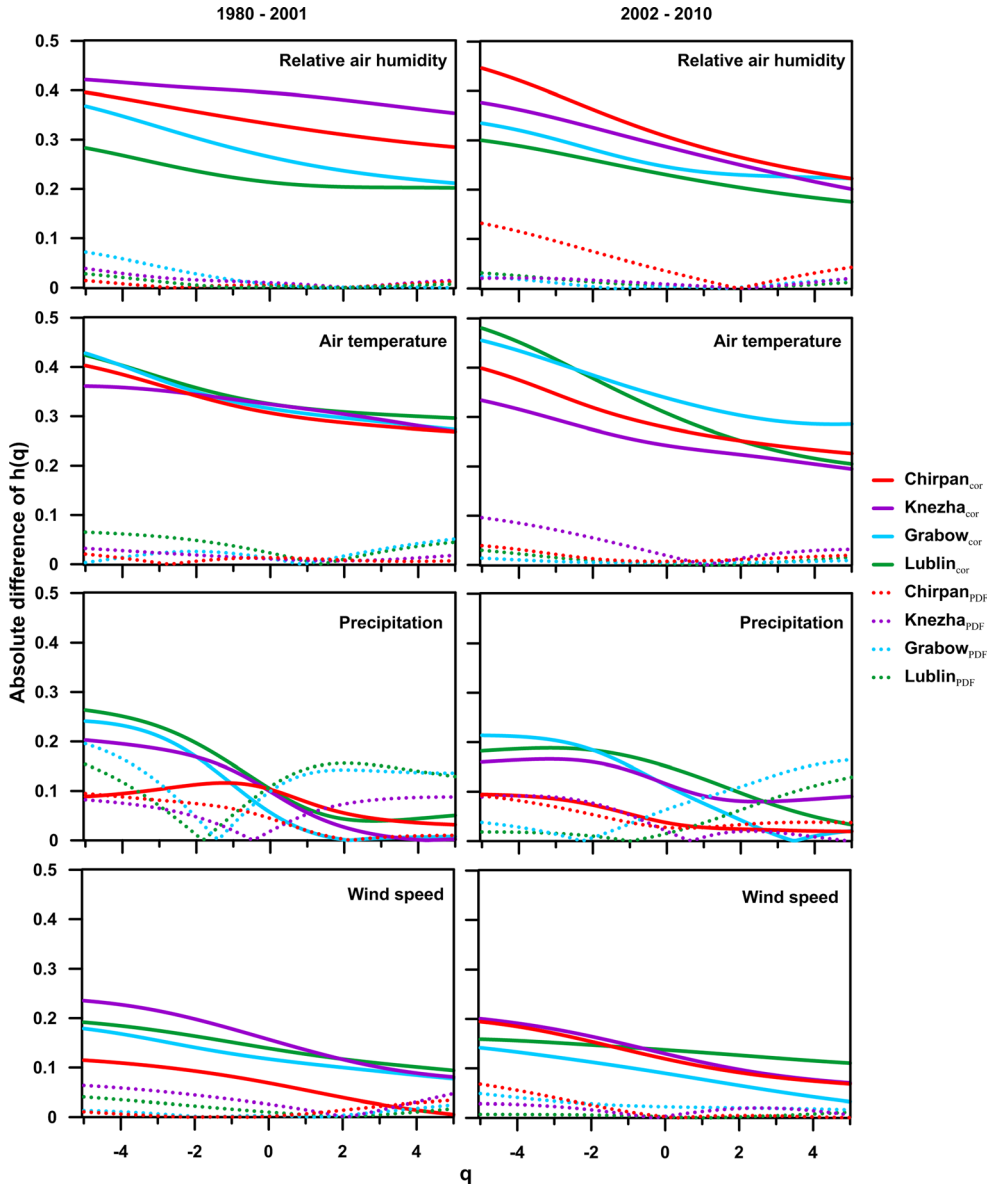

Fig. 7 Absolute differences of Hurst exponents for the original and shuffled data $|h(q) - h_{shuf}(q)| = |h_{COR}(q)|$ and the original and surrogate data $|h(q) - h_{sur}(q)| = |h_{PDF}(q)|$ as a function of q for all studied meteorological time series in two periods: the left panel for the 1980–2001 period, the right panel for the 2002–2010 period

second sub-period. The observed changes suggest that MF-DFA has a potential to assess the variations in the dynamics of weather processes of time series located in varied climatic zones or before and after the climatic shifts, but to what extent it depends mainly on the analyzed quantity.

4 Conclusions

The obtained results strongly suggest that the studied meteorological quantities possess specific time and space dynamics that exhibit the property of self-similarity. This is an intrinsic feature of the analyzed meteorological time series, as the multifractality manifested itself for all of the quantities and did not depend on the site or the time period of the recorded data.

Multifractality of such meteorological elements as relative air humidity or air temperature time series stem from the long-distance power-law correlations. This kind of correlations is also a dominant source of the wind speed time series multifractality, but their influence is lesser. Of course, multifractality due to a broad PDF is present in these time series as well, but its impact is only minor. In turn, our findings indicate that the multifractal spectrum of precipitation varies considerably from the spectra of other analyzed climate variables, as for precipitation, the multifractality is driven by both sources, i.e., the broadness of the PDF and the long-distance power-law correlations, at least to the same extent. As climate change for sure impacts the PDFs of the time series, the above results strongly suggest that precipitation is a meteorological element more sensitive to changes in the dynamics of the climate than other analyzed climatic quantities.

The presented analysis also reveals country specificity of the parameters describing the multifractal spectra, which is the evidence that MF-DFA is a method being capable to spot spatial variabilities of the dynamics of processes governing the atmosphere. In several instances (i.e., for meteorological quantities or parameters describing the multifractal spectra), the local climate characteristics manifested themselves more strongly than the regional ones related to temperate and semi-arid zones, but still, country congruence occurs for relative air humidity, precipitation, and air temperature (in case of air temperature such a feature was not noticed only in the width of the spectra w).

It was also established that the MF-DFA is sensitive to climatic shifts, as the spectra parameters of the time series divided into two subsets, differed considerably. It allows to state that the MF-DFA method can be used to assess qualitatively or even quantitatively the differences in the dynamics of atmospheric processes. Referring to the values of α_0 or the width of the spectrum w, no consistent changes were observed. This result implies that the impact on these two features was more from the local (climatic zones) than global changes in climate dynamics. However, the changes in the asymmetry parameter a_s are more consistent and tend to change towards either less positive or even negative values, which clearly indicates that more extreme events are present or even dominate in the time series. The obtained singularity, spectra have led to a better description of the structure of the series, revealing noticeable modification of multifractal parameters after the climatic shift.

Because the results confirm differentiation of the multifractal characteristics of basic meteorological quantities depending on location and time lags, further studies of long-term climatic records from the network of stations located in a wider variety of climate zones are expected. Such an attempt, which is planned by the authors in future, will enable to detect differences in the multifractal properties of these series depending on climate zones or even to map them.

Funding information This paper has been supported within the framework of the Polish-Bulgarian Joint Research Project for the years 2015–2018 "Impact of climate change and adaptation of some sectors of national economy in Poland and Bulgaria" under the agreement on scientific cooperation between the Polish Academy of Sciences and the Bulgarian Academy of Sciences and has been partly financed from the funds of the Polish National Centre for Research and Development within the framework of the projects: LCAgri, contract number: BIOSTRATEG1/271322/3/NCBR/2015 and GyroScan, contract number: BIOSTRATEG2/298782/11/NCBR/2016.

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