



A multifractal cross-correlation investigation into sensitivity and dependence of meteorological and hydrological droughts on precipitation and temperature

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Abstract

Several studies have been conducted on droughts, precipitation, and temperature, whereas none have addressed the underlying relationship between nonlinear dynamic properties and patterns of two main hydrological parameters, precipitation and temperature, and meteorological and hydrological droughts. Monthly datasets of Midlands in the UK between 1921 and 2019 were collected for analysis. Subsequent to apply a multifractal approach to attain the nonlinear features of the datasets, the relationship between two hydrological parameters and droughts was investigated through the cross-correlation technique. A similar process was performed to analyze the relationship between multifractal strength variations in time series of precipitation and temperature and droughts. The nonlinear dynamic results indicated that droughts (meteorological and hydrological) were substantially affected by precipitation than temperature. In other words, droughts were more sensitive to precipitation fluctuations than temperature fluctuations. Concerning temperature, meteorological, and hydrological droughts were dependent on the minimum and maximum temperatures (T_{\min} and T_{\max}), respectively. The correlation between precipitation and meteorological drought was more long-range persistence than precipitation and hydrological drought. Besides, the correlation between T_{\max} and droughts was more long-range persistence than T_{\min} and droughts. Analysis of nonlinear dynamic patterns proved that the multifractal strength of meteorological drought depended on the multifractal strength of precipitation and T_{\max} , whereas the multifractal strength of hydrological drought depended on the multifractal strength of the T_{\min} . The correlation between precipitation and drought indices exhibited more multifractal strength than temperature and drought indices. Finally, the pivotal role of maximum temperature on drought events was quite alerting due to global warming intensification.

Keywords Pearson correlation coefficient · Spearman rank correlation coefficient · Multifractal detrend fluctuation analysis (MF-DFA) · Multifractal detrended cross-correlation analysis (MF-DXA) · Standard precipitation index · Streamflow drought index

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1 Introduction

Drought as a complex and multifaceted event provokes considerable damage to agriculture, natural resources, and society (Li et al. 2015; Yu et al. 2016; An and Hao 2017; Byakantonda et al. 2018; Rahmani and Fattahi 2021). Climate change has induced massive alterations in temperature and precipitation behavior patterns, which has resulted in an increment in the occurrence of extreme phenomena (Li et al. 2020; Zhao et al. 2018; Ahmed et al. 2018). Therefore, drought forecasting and monitoring are significant and relevant; various studies have been conducted to monitor and predict drought in diverse catchments (Hao et al. 2017a, b; Tian et al. 2018; Aghelpour et al. 2020; Hao et al. 2018; Xu et al. 2018; Malik et al. 2019; Agana et al. 2017). On average, UK experiences a meteorological or hydrological drought every 5 to 10 years. From 1900 to 2015, twelve and three significant meteorological and hydrological droughts occurred in the UK, respectively. Details concerning recorded droughts are provided in Table 1.

There are numerous definitions of meteorological and hydrological droughts varying based on the spatial and temporal of droughts. More limited than typical precipitation leading to alterations in climate patterns in a basin is a traditional interpretation of meteorological drought suggested by meteorological experts. A more accurate definition of meteorological and hydrological drought is that if precipitation or runoff of each year reduces by more than 35% compared to the long-term average leading up to that year, it is called meteorological and hydrological drought, respectively. It has been proved that hydrological and meteorological droughts are directly associated with the hydrological basin characteristics and climate of the study catchment (Van Loon and Laaha 2015; Yang et al. 2017); and recently, the relationship between meteorological and hydrological droughts has been investigated (Liu et al. 2019a, b; Bhardwaj et al. 2020; Peña-Gallardo et al. 2019a, b). However, the multifractal variations' impact of temperature and precipitation on the multifractality of meteorological and hydrological drought hitherto has not been studied. The aforementioned will reveal the extent to which meteorological and hydrological droughts

Table 1 Droughts recorded from 1900 to 2015 in the UK (see www.metoffice.gov.uk)

	Time interval	Start month	End month	Affected area	Drought type
1	1920–1921	Aug	Dec	UK	Meteorological
2	1933–1934	Apr	Nov	UK	Meteorological
3	1943–1944	Feb	Jul	UK	Meteorological
4	1947–1949	Aug	Sep	UK	Meteorological
5	1963–1965	Dec	Feb	UK	Meteorological
6	1972–1974	Aug	May	UK	Meteorological
7	1975–1976	May	Aug	UK	Meteorological
8	1988–1989	Aug	Nov	UK	Meteorological
9	1990–1992	Mar	Feb	UK	Meteorological
10	1995–1997	Apr	Apr	UK	Meteorological
11	2004–2006	Nov	Apr	UK	Meteorological
12	2010–2012	Apr	Mar	UK	Meteorological
13	1995–1998	Summer	Winter	UK	Hydrological
14	2003–2006	Summer	Winter	UK	Hydrological
15	2010–2012	Winter	Winter	UK	Hydrological

are sensitive (dependent) to pattern variations in temperature and precipitation. Moreover, it is of great significance for better understanding the drought mechanism, drought prediction, and its severity, to assess and manage the risk and consequences of drought, as well as hydrological studies.

Multifractality is the essence of natural phenomena, and studies have designated that hydrological parameters such as precipitation (Zhang et al. 2021; Morales Martinez et al. 2021), temperature (Santos da Silva et al. 2020; Toluwalope Ogunjo et al. 2021), and drought (Adarsh et al. 2019; Tatli and Dalfes 2020; Adarsh and Priya 2021; Toluwalope Ogunjo et al. 2021; Hou et al. 2018) have multifractal properties. The multifractal theory, associated with chaos theory, was advanced by Mandelbrot in the early 1970s.

The cross-correlation technique is a valuable tool for finding the hidden connection between two time series, by which the underlying association reveals between two phenomena or two simultaneously recorded signals. Several studies have been conducted on droughts that used the cross-correlation technique for prediction and studying agricultural, meteorological, and hydrological droughts (Crow et al. 2012; Stefan et al. 2004; Zarei et al. 2021; Uddin et al. 2020; Nabipour et al. 2020; Ullah et al. 2021). Multifractal detrended cross-correlation analysis (MF-DXA) is known as a practical technique for detecting the multifractal properties of two cross-correlated time series. This method is used for cross-correlated nonstationary series, applying polynomial fitting to eliminate the trends in time series. This theory has been employed to study on future market of energy (Wang et al. 2019), global methane and temperature (Tzani et al. 2020), air pollutants (Manimaran and Narayana 2018), Bitcoin market (Zhang et al. 2018), carbon market future in Europe (Zou and Zhang 2020), RMB exchange rates (Xie et al. 2017), streamflow and sediment fluctuation (Wu et al. 2018), river level records (Wu et al. 2020), the temperature anomalies and the SENSEX fluctuations (Chatterjee and Ghosh 2021), North Atlantic oscillation and precipitation (Tatli and Menteş 2019).

Met Office (the Met Office is the national meteorological service for the UK providing weather services and world-leading climate science) provides UK State of the Climate report annually. This governmental institution has recently published a report (Kendon et al. 2020) providing information on climate trends and observational data concerning climate quality in the UK. This report ignored the invisible mechanism between climatic parameters (precipitation, temperature, meteorological and hydrological droughts) and failed to examine the impact (sensitivity) of precipitation and temperature on droughts. In addition, this report paid scant attention to the nonlinear dynamic patterns of precipitation and temperature and their influence on the behavioral patterns of meteorological and hydrological droughts. In conclusion, the report delivered a superficial understanding of the climate parameters in the region (to be specific, precipitation, temperature, meteorological and hydrological droughts), whereas this study provided a profound perception of the underlying mechanisms governing the relationship between precipitation and temperature and meteorological and hydrological droughts. This study investigated the sensitivity (dependency) of meteorological and hydrological droughts to temperature and precipitation, as well as meteorological and hydrological droughts multifractality dependence on the multifractal variations in precipitation and temperature. It was conducted to reveal 1—the nonlinear dynamic patterns governing the climate of the study area; 2—the variation in the nonlinear dynamic behavior of precipitation and temperature after how long brings about a difference in the patterns of hydrological and meteorological droughts in the study area; 3—how strongly alterations in precipitation and temperature patterns affect droughts patterns (in other words, the severity of meteorological and hydrological droughts can be estimated by observing anomalies magnitude in the precipitation and temperature patterns);

4—the hidden correlation between precipitation and temperature and meteorological and hydrological droughts, and the latent effects of nonlinear dynamic behavioral patterns governing precipitation and temperature on meteorological and hydrological droughts patterns. Accordingly, this study serves to predict meteorological and hydrological droughts more efficiently and develop drought prediction methods by expanding our understanding of the underlying mechanisms governing the relationship between precipitation and temperature meteorological and hydrological droughts.

Standard Precipitation Index (SPI) and Streamflow Drought Index (SDI) were employed to estimate meteorological and hydrological droughts, respectively. To examine multifractal strength variations in precipitation and temperature time series, correlation analysis of meteorological and hydrological droughts with precipitation and temperature, multifractal detrended fluctuations analysis (MF-DFA), Pearson correlation coefficient (PCC), and Spearman rank correlation coefficient were employed, respectively. Additionally, to estimate droughts' multifractal strength variations dependence on multifractal strength variations in precipitation and temperature, and cross-correlation among time series, cross-correlation, and multifractal detrended cross-correlation analysis (MF-DXA) techniques were applied, respectively.

The study is separated into five main segments. Chapter 2 discusses details concerning the study area, data sources, and theoretical and analytical details regarding cross-correlation, MF-DFA, MF-DXA, SPI, and SDI. In part 3, the results and discussions are presented, and finally, a summary and conclusion are delivered in chapter 4.

2 Materials and methods

The employed precipitation, temperature, and river flow data were associated with the Midlands in the UK (Fig. 1). The data were monthly and considered between 1921 and 2019 (99 years), and precipitation and temperature datasets and river flow data were collected from www.metoffice.gov.uk and www.nrfa.ceh.ac.uk websites, respectively. The Midlands area embraces the Peak District, the Cotswold Hills, and the Northamptonshire, toward the north, south, and east, respectively. The Midlands area is bounded by the Welsh border to the west. Mean annual temperatures over the study area vary from 8 °C to over 10 °C. The wettest and the driest areas in the Midlands experience, on average, 800- and 600-mm precipitation per year, respectively (for further details, see www.metoffice.gov.uk). Gauged daily flow data (m³/s) related to station Severn at Bewdley (ID 54,001, see www.nrfa.ceh.ac.uk), and daily data were converted to monthly to fit the drought estimation.

Since the long-term correlations and the multifractal spectrum width (for multifractal strength estimation) are strongly susceptible to the periodicities in hydrological time series, the Seasonal and Trend decomposition using Loess (STL) technique suggested by Cleveland et al. (1990) was employed to eliminate the periodic seasonal trends in temperature and precipitation time series. Following, hydrological and meteorological droughts were estimated using SDI and SPI, respectively. To evaluate the multifractal strength variations in temperature, precipitation, and drought indices, multifractal detrended fluctuation analysis (MF-DFA) was employed. Pearson correlation coefficient (PCC), Spearman rank correlation coefficient (SRCC), and cross-correlation technique, and multifractal detrended cross-correlation analysis (MF-DXA) were applied for correlation and cross-correlation evaluation between time series and persistency determination of cross-correlation between time series, respectively. The PCC method examines the correlation based on the linear relationship and linear trend between

Fig. 1 Selected region in the UK, marked with a green area (see www.metoffice.gov.uk)



time series. PCC values are ranged between -1 and 1. PCC equal to zero indicates the absence of correlation between the two time series. Values close to 1 and -1 indicate a strong dependency and correlation between the two time series, in which negative and positive values represent the negative and positive correlation between the two series, respectively.

SRCC suggests a nonparametric method, evaluating the statistical rank correlation between two sets of rankings. SRCC assesses linear or nonlinear monotonic relationships between two time series. SRCC values and their interpretation are the same as the PCC method, with the difference that it describes the monotonic relationship between time series.

The cross-correlation function can be applied to assess the similarity between a time series and lagged versions of another time series as a function of the lag. Suppose the time series y_{1a} and y_{2a} and lags l where $l = 0, \pm 1, \pm 2, \dots$. For data pairs $(y_{11}, y_{21}), (y_{12}, y_{22}), \dots, (y_{1N}, y_{2N})$, cross-correlation can be computed based on the sample standard deviations and the lag l cross-covariance (Eqs. (1–2)):

$$\begin{aligned}
 S_{y_1} &= \sqrt{C_{y_1y_2}(0)}, \text{ where } C_{y_1y_2}(0) = \text{Var}(y_1) \\
 S_{y_2} &= \sqrt{C_{y_2y_2}(0)}, \text{ where } C_{y_2y_2}(0) = \text{Var}(y_2)
 \end{aligned}
 \tag{1}$$

$$r_{y_1y_2}(l) = \frac{C_{y_1y_2}(l)}{S_{y_1}S_{y_2}} ; \quad l = 0, \pm 1, \pm 2, \dots
 \tag{2}$$

where $C_{y_m y_n}$, S_{y_m} , and $r_{y_m y_n}$ are the lag l cross-covariance, the sample standard deviations, and cross-correlation, respectively.

In the following, the utilized drought indices and multifractal techniques will be introduced.

2.1 Standard precipitation index (SPI) and Streamflow drought index (SDI)

Standard Precipitation Index (SPI) and Streamflow Drought Index (SDI) were introduced by McKee (1993) and Nalbantis (2009), respectively, to determine duration, severity, and intensity of meteorological and hydrological drought in a catchment at multi-timescales. SPI is based on the probability density function and the gamma distribution. The transformed probability density function and the gamma distribution to the standard normal distribution are represented by Z , addressing the SPI (Harisuseno 2020). Z is characterized as Eq. (3):

$$Z = SPI = - \left(t - \frac{c_0 + c_1 + c_2 t^2}{1 + d_1 t + d_2 t^2 + d_3 t^3} \right) \tag{3}$$

where c and d are constant and t is calculated based on the probability density function and the gamma distribution.

The computational process difference between SPI and SDI is that in SPI, the values of precipitation are applied, while in SDI, the values of river flow are applied. SDI can be estimated by Eq. (4) (Ozkaya and Zerberh 2019):

$$SDI_{i,k} = \frac{V_{i,k} - \bar{V}_k}{S_k} \quad i = 1, 2, \dots \quad k = 1, 2, \dots \tag{4}$$

k and i show the months and years, respectively, and $V_{i,k}$, \bar{V}_k , and S_k are the cumulative streamflow volumes, mean, and standard deviation of cumulative streamflow volumes, respectively.

Drought can be classified as follows based on SPI and SDI values (Table 2).

In this study, to scrutinize the meteorological and hydrological droughts, the values of SPI and SDI were calculated and applied monthly. To evaluate SPI and SDI, DrinC software (Tigkas et al. 2015) was employed, which is available at <https://drought-softw are.com/download/>.

Table 2 Drought’s classifications based on SPI and SDI values (Tigkas 2008)

Values of SPI and SDI	Class description
+2.0 and more	Extremely wet
+1.5 to +1.99	Very wet
+1.00 to +1.49	Moderately wet
+0.5 to +0.99	Mild wet
− 0.49 to +0.49	Normal
− 0.5 to −0.99	Mild drought
− 1.0 to − 1.49	Moderate drought
− 1.5 to − 1.99	Severe drought
− 2.0 and less	Extreme drought

2.2 Multifractal detrended fluctuation analysis (MF-DFA)

Detrended fluctuation analysis (DFA) method is widely used for the determination of monofractal scaling features and discovering long-range correlations in noisy, nonstationary time series (Kantelhardt et al. 2002). In geo-physical phenomenon including hydrologic processes which are expressing in time series formation, the complexity of multitime scaling behaviors makes it necessary to employ a multifractal approach to fully describe these interwoven connections. The multifractal detrended fluctuation analysis (MF-DFA) method is regularly exercised for estimation of the multifractality in the time series. MF-DFA method is acknowledged as the most effective technique for multifractality determination of time series and its appropriate function for nonstationary time series analysis (Adarsh et al. 2020; Miloş et al. 2020), making this technique proper for multifractal analysis of hydrological time series. Consequently, we employed the MF-DFA method to examine multifractal strength in time series. The singularity spectrum $f(\alpha)$ is a mechanism for representing the multifractality of a time series. The singularity spectrum is assessed based on the scaling exponent $\tau(q)$, and first-order Legendre transforms (Eq. (5)) and registers the time series segment dimensions distinguished by α (see Eq. (6)). Moreover, the width of $f(\alpha)$ denotes the strength of the multifractality in a time series. Essentially, if $f(\alpha)$ is a single point, then the time series is monofractal.

$$\tau(q) = q \times H(q) - 1 \tag{5}$$

$$\alpha = \frac{\partial \tau(q)}{\partial q}, f(\alpha) = \alpha q - \tau(q) \tag{6}$$

where α is perceived to be the Hölder exponent (singularity index) and q is the order weighting the local variations. $H(q)$ represents the generalized Hurst exponent and is defined by Eq. (7).

$$F_q(s) \propto s^{H(q)} \tag{7}$$

Equation 7 is the power-law relationship between fluctuation segment $F_q(s)$ and time-scale s . The slope of the fitted $F_q(s)$ and s estimates $H(q)$.

The singularity index is utilized extensively to mark the degrees of the singularity of the time series. The width of $f(\alpha)$ is exposed by $\Delta\alpha$ and details related to the distribution evenness of the prospect of the fractal formation. The higher the value of $\Delta\alpha ((\alpha_{max} - \alpha_{min}))$, the more substantial the multifractality and complexity of the time series. It involves an asymmetrical time series with more severe fluctuations. $\Delta\alpha$ was measured to estimate the multifractality of each window.

The graphs of the $H(q) \sim q$ depict monofractal or multifractal behavior of the time series. A time series is multifractal when $H(q)$ is dependent on the q values. Despite this, $H(q)$ independency on the q values shows monofractality of the time series. The positive q for $H(q)$ is granted to interpret the scaling behavior of fragments, which comprises considerable fluctuations. However, negative q is accepted to elucidate the scaling behavior of sections holding miniature fluctuations (Livina et al. 2007; Sun et al. 2001). To assess the multifractal strength variations in the time series, a fixed-size window was considered (for illustration, a window with 6-month long or lag=6). This window was then moved from the beginning to the end of the time series and the multifractal strength was estimated in each window.

2.3 Multifractal detrended cross-correlation analysis (MF-DXA)

In 2008, the multifractal detrended cross-correlation analysis (MF-DXA) theory was introduced by Zhou. This method was suggested to assess the multifractal behaviors in the power-law cross-correlations between two signals, which is suitable for analyzing complex systems, including finance, ecology, physiology, geohydrology, and hydrology.

Suppose two time series $x(i)$ and $y(i)$ with the same length. The profile for calculation MF-DXA is shown in Eq. (8) (see (Zhou 2008)):

$$X(i) = \sum_{t=1}^i (x(t) - \bar{x}), \quad Y(i) = \sum_{t=1}^i (y(t) - \bar{y}), \quad i = 1, 2, \dots, N \quad (8)$$

\bar{x} and \bar{y} represent the sample means, and N represents the time series length. In the next step, $X(i)$ and $Y(i)$ subsequences are divided into cell of length s , while the cells should not have any overlap. The similar process is repeated starting from the other end of the time series due to timescale s that may not be a multiple of N (Cao and Shi 2017). To obtain the q -order fluctuation function, averaging should be applied through all segments (Eq. (9)).

$$F_q(s) = \begin{cases} \left\{ \frac{1}{2N_s} \sum_{v=1}^{2N_s} [F^2(s, v)]^{q/2} \right\}^{\frac{1}{q}} & q \neq 0 \\ \exp \left\{ \frac{1}{4N_s} \sum_{v=1}^{2N_s} \ln [F^2(s, v)] \right\} & q = 0 \end{cases} \quad (9)$$

where $F^2(s, v)$ is the variance of each segment v .

For two long-range cross-correlated time series, according to the power-law, $F_q(s)$ values augment for large s values (Eq. (10)).

$$F_q(s) \sim S^{H_{xy}(q)} \rightarrow \log F_q(s) = H_{xy}(q) \log(s) + \log A \quad (10)$$

The power-law connection between two recorded signals (time series) is described by the generalized Hurst cross-correlation exponent, which is shown in Eq. (10) by $H_{xy}(q)$. The interpretation of $H_{xy}(q)$ values and $H(q)$ values in the MF-DFA method is similar, with the difference that $H_{xy}(q)$ determines the multifractality and persistency properties of cross-correlation between two time series.

MATLAB software was utilized to estimate cross-correlation, PCC, SRCC, MF-DFA, and MF-DXA.

3 Results and discussion

First, meteorological and hydrological droughts (SPI and SDI, respectively) were analyzed in the study area. Then, correlation, cross-correlation, and cross-correlation persistency were evaluated between hydrological parameters (precipitation, maximum temperature, and minimum temperature) and meteorological and hydrological droughts (SPI and SDI, respectively) to investigate the susceptibility of meteorological and hydrological droughts (SPI and SDI, respectively) to precipitation, maximum temperature, and minimum temperature. Subsequently, the identical process was applied to multifractal strength variations in the aforementioned data. Table 3 exposes the abbreviations adopted in this study, which

Table 3 Utilized abbreviations and the meanings

Abbreviation	Meaning
$S_{x,y}$	Spearman’s value between time series x and y
$P_{x,y}$	Pearson’s value between time series x and y
$H_{x,y}$	Generalized Hurst exponent’s value between time series x and y calculated by MF-DXA
T_{max}	Maximum temperature
T_{min}	Minimum temperature

from now on the results are presented based on these abbreviations. The analysis steps are illustrated in Fig. 2.

First, the drought analysis results are presented, and then the sensitivity analysis results will be reviewed. According to the Met Office data, the average annual precipitation, maximum temperature, and minimum annual temperature in the UK from 1961 to 2010 were 1126.9 mm, 12.6 °C, and 5.07 °C, respectively. However, the computed average annual precipitation, maximum temperature, and minimum temperature for the Midlands were 780.86 mm, 13.07 °C, and 5.38 °C, respectively. It indicated that the study area was drier and warmer (lower average precipitation and higher average temperature) than the entire UK.

As shown in Fig. 3a, the study area experienced five severe or extreme dry months and two very wet months between 1921 and 1923. By examining the fluctuations trend of SPI and SDI, it was revealed that the impact of meteorological dry or wet months affected the hydrology of the region with a delay of one to three months. A similar examination was conducted for subsequent years and confirmed the mentioned results. The general trend of SPI and SDI fluctuations registered that the fluctuations had an

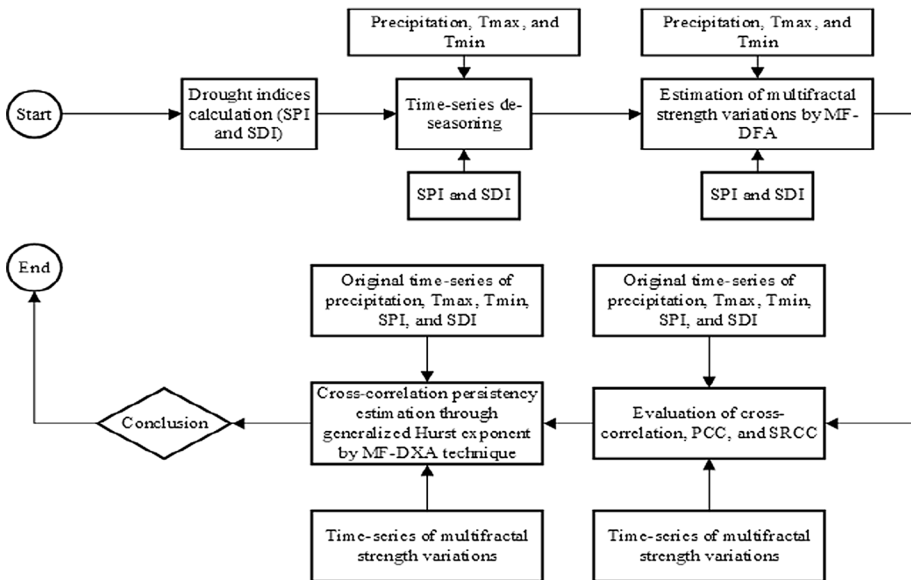


Fig. 2 Analysis steps for evaluation of meteorological and hydrological drought sensitivity to precipitation, T_{max} , T_{min} , and multifractal strength variations in the time series

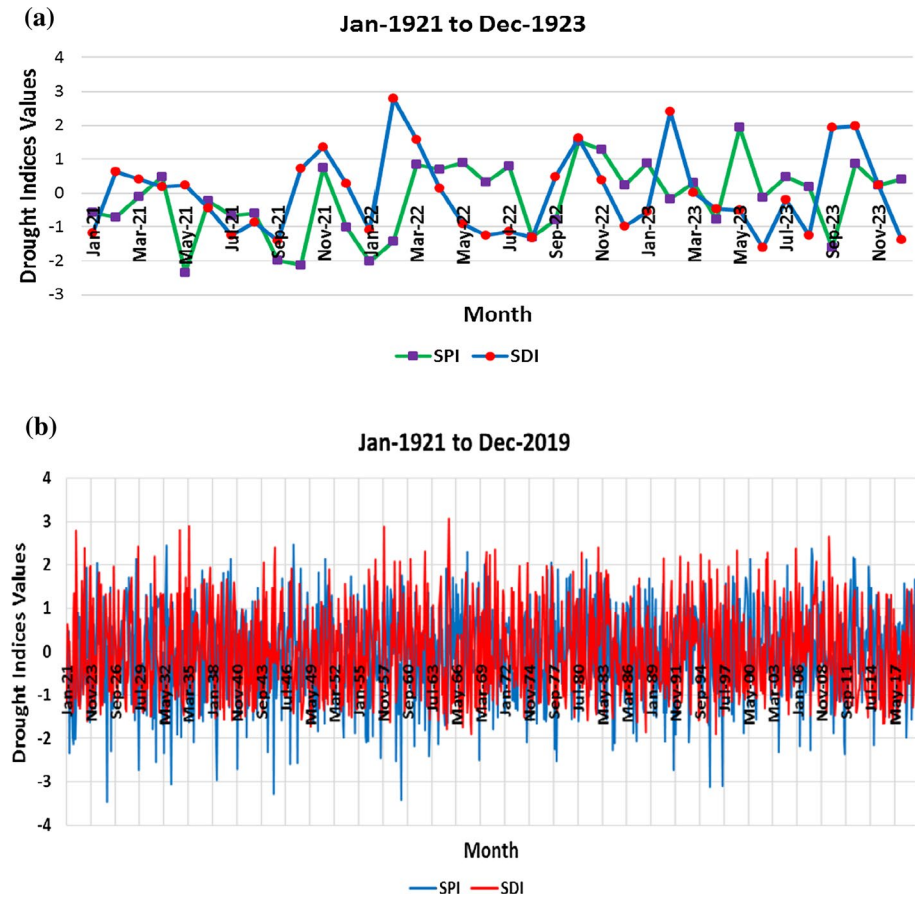


Fig. 3 SPI and SDI values for short- (1921–1923) (a) and long-term (1921 to 2019) (b) concerning Midlands in the UK

upward trend and a slope equal to 3×10^{-6} . The fluctuations of SPI were much more severe than the SDI fluctuations (Fig. 3b).

Examination of anomalies in the monthly precipitation time series revealed that the number of anomalies (significant precipitation in a month; total precipitation above 150 mm in one month was considered an anomaly) in one year decreased over time. On the other hand, the number of anomalies in the minimum and maximum temperature time series (extremely high or notably low temperature in a month; concerning maximum temperature, temperatures above 23 °C and temperatures below 3 °C were considered anomalies, and concerning minimum temperature, temperatures above 12 °C and temperatures below – 2 °C were considered anomalies) increased. These anomalies can be seen in Fig. 4.

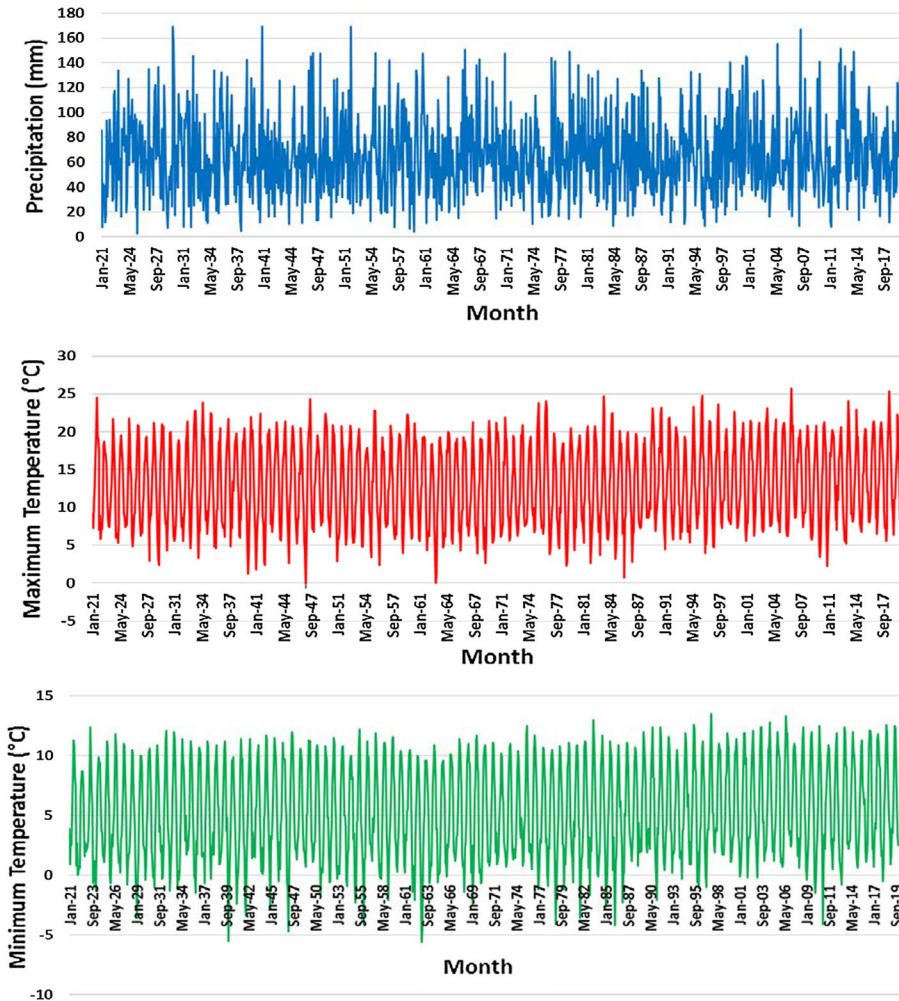


Fig. 4 Monthly precipitation graphs, average monthly maximum temperature, and average monthly minimum temperature for Midlands in the UK between 1921 and 2019

3.1 Results of Pearson, Spearman, Cross-Correlation, and Hurst’s values concerning precipitation and temperature time series

To investigate the dependency and sensitivity of meteorological and hydrological droughts to precipitation and temperature, Hurst exponent, Pearson correlation coefficient (PCC) (see Benesty et al. 2009), Spearman rank correlation coefficient (SRCC) (see Lyerly 1952), and cross-correlation were estimated for hydrological datasets (precipitation, T_{max} and T_{min}) and drought indices (SPI and SDI) time series, the results of which are sorted in Table 4 and Fig. 5.

To describe Spearman and Pearson’s values, the word Pre is used instead of precipitation. The values of $P_{Pre, SPI}$, $P_{Pre, SDI}$, $P_{Tmax, SPI}$, and $P_{Tmax, SDI}$ were negative (Table 4),

Table 4 Generalized Hurst exponent, PCC, and SRCC's values concerning precipitation and temperature time series and drought indices

	y series	x series		
		Precipitation	T_{\max}	T_{\min}
$H_{x,y}$	<i>SPI</i>	0.8261	0.7508	0.7339
	<i>SDI</i>	0.7467	0.7367	0.7207
$P_{x,y}$	<i>SPI</i>	− 0.0996	− 0.0012	0.0022
	<i>SDI</i>	− 0.0072	− 0.0028	0.0018
$S_{x,y}$	<i>SPI</i>	− 0.0902	0.0034	0.0062
	<i>SDI</i>	0.0038	− 0.0055	− 0.0032

indicating the presence of a negative (reverse connection) linear relationship between the two time series. The values of $P_{T_{\min}, SPI}$ and $P_{T_{\min}, SDI}$ were positive, suggesting a level of positive (direct connection) linear correlation between the two time series. The correlation between precipitation time series and drought indices was higher than temperature time series. This was indicative of a stronger linear relationship between precipitation and droughts. In other words, in the study area, meteorological and hydrological droughts were more susceptible to precipitation fluctuations than temperature fluctuations. Precipitation and T_{\min} had a stronger linear correlation (negative and positive, respectively) with meteorological drought than hydrological drought. Moreover, hydrological drought exposes more correlation (a negative linear correlation) to T_{\max} than meteorological drought.

Table 4 illustrates that the values of $S_{Pre, SPI}$, $S_{T_{\max}, SDI}$, and $S_{T_{\min}, SDI}$ were negative. It provided evidence for a negative monotonic relationship between precipitation and meteorological drought and temperature and hydrological drought. On the contrary, the values of $S_{Pre, SDI}$, $S_{T_{\max}, SPI}$, and $S_{T_{\min}, SPI}$ were positive, implying that temperature and meteorological drought and precipitation and hydrological drought are monotonically related. Besides, the values of $S_{Pre, SPI}$ and $S_{T_{\min}, SPI}$ were higher than $S_{Pre, SDI}$ and $S_{T_{\min}, SDI}$. It would suggest that, in the study area, meteorological drought exhibited a potent monotonical relation with precipitation and T_{\min} . However, the value of $S_{T_{\max}, SPI}$ was less than $S_{T_{\max}, SDI}$, drawing a conclusion of an effective monotonical relation between T_{\max} and hydrological drought.

Figure 5 illustrates the cross-correlation values between precipitation and temperature time series and drought indices. It was obvious from Fig. 5 that the cross-correlation between precipitation and drought indices was higher than temperature and drought indices. Besides, the cross-correlation between precipitation and SPI was more substantial than precipitation and SDI (the maximum cross-correlation value and red lines crossed confidence bounds). It implied that meteorological drought showed more sensitivity to precipitation in comparison with hydrological drought. The maximum cross-correlation between precipitation and SPI was at lag 3, while between precipitation and SDI was at lag 19. The former supported the notion that precipitation fluctuations affected meteorological drought (first) and hydrological drought (subsequently) with a delay of 16 months.

More sensitivity of hydrological drought to temperature than meteorological drought to temperature was inferred from stronger cross-correlation between temperature and SDI than temperature and SPI. The cross-correlation between T_{\max} and SDI was more solid (more values bigger than confidence bounds) than T_{\min} and SDI, indicating more sensitivity of hydrological drought to T_{\max} than T_{\min} . The cross-correlation between temperature and SPI was negligible, and the maximum cross-correlation between temperature and SDI was

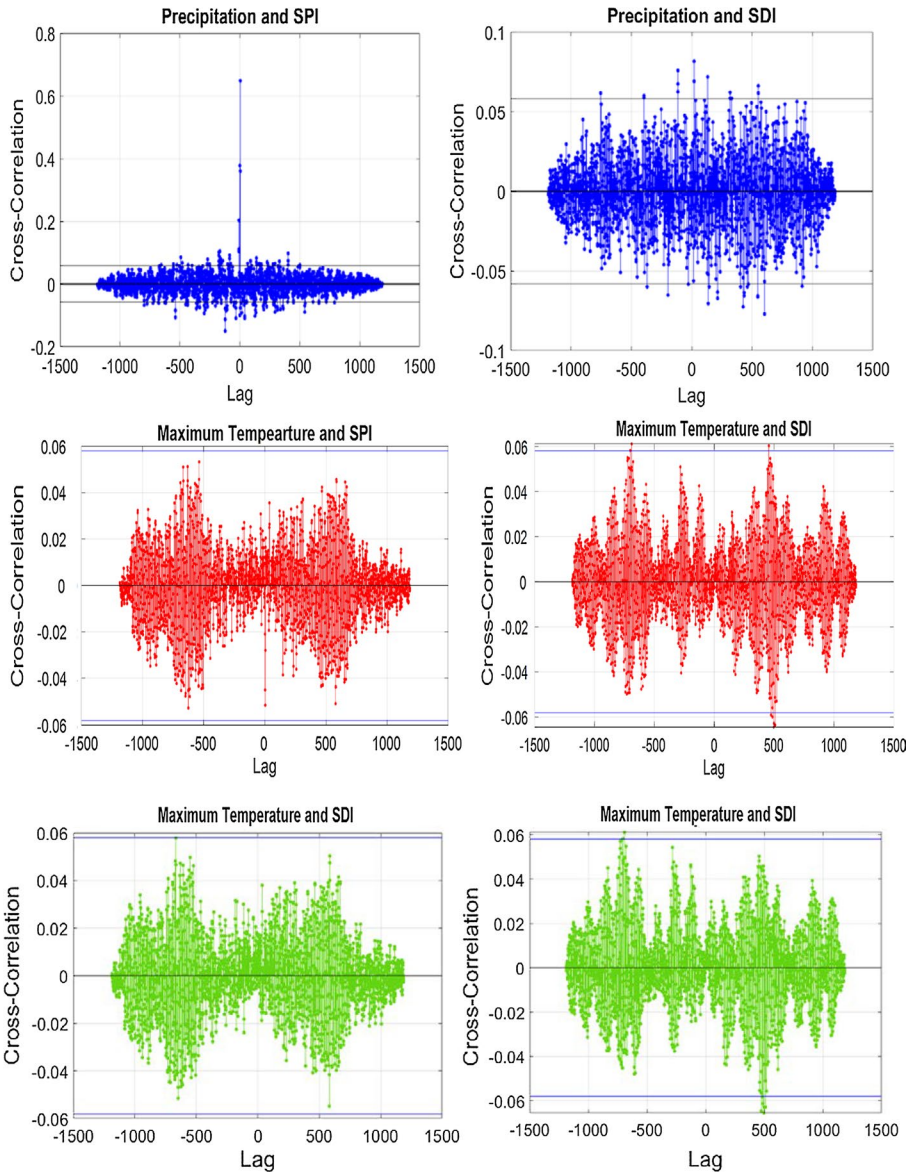


Fig. 5 The cross-correlation graphs concerning precipitation and temperature time series and drought indices (the blue horizontal lines are confidence bounds consisting of 2 standard errors)

at lag 498 (maximum cross-correlation values concerning T_{max} and T_{min} were -0.0645 and -0.0656, respectively.)

The time series persistency was investigated by application of the Hurst exponent, and the results are provided in Table 4. As shown in Table 4, H_{SPI} values were higher than H_{SDI} values. It supported that precipitation and temperature registered cross-correlation with a stronger long-range persistency with meteorological than hydrological

drought. Besides, $H_{Pre,SPI}$ and $H_{Pre,SDI}$ held the highest values, corroborating a cross-correlation with long-range persistency between precipitation time series and drought indices.

A long-range persistent cross-correlation between T_{max} and drought indices was inferred from greater values of $H_{Tmax,SPI}$ and $H_{Tmax,SDI}$ than $H_{Tmin,SPI}$ and $H_{Tmin,SDI}$. The cross-correlation between meteorological drought and precipitation exhibited more long-range memory than hydrologic drought and precipitation, concluded from the higher value of $H_{Pre,SPI}$ than $H_{Pre,SDI}$. The Hurst values confirmed linear, monotonic, and sensitivity analysis results concerning relationship between precipitation and temperature and drought indices. It was verified that there was an influential association between meteorological drought and precipitation.

To evaluate the timescale influences on Hurst’s values and time series multifractality, four timescales were considered (6–24 months (2 years), 6–60 months (5 years), 6–120 months (10 years), and 6–228 months (19 years)) (Table 5). The results proved that the cross-correlation long-range persistency intensified between hydrological series and drought indices owing to the reduction in scale length. However, the multifractal strength declined as a cutback in scale length except for the 6–24 months scale. At the 6–24 months scale, $\Delta\alpha_{Tmax,SPI}$, $\Delta\alpha_{Tmin,SPI}$, $\Delta\alpha_{Tmax,SDI}$, and $\Delta\alpha_{Tmin,SDI}$ experienced increments. The $\Delta\alpha$ positive values for all scale-lengths provided evidence for more probability of large local fluctuations than small local fluctuations in the time series.

Table 5 Generalized Hurst exponent and multifractal strength’s values concerning hydrological time series and drought indices

Scale	y series		x series		
			Precipitation	T_{max}	T_{min}
6–24 months (2 years)	$H_{x,y}$	<i>SPI</i>	0.9515	0.9695	0.9449
		<i>SDI</i>	0.9245	0.9435	0.9103
	$\Delta\alpha_{x,y}$	<i>SPI</i>	1.5870	1.9662	1.8963
		<i>SDI</i>	1.6172	2.0480	1.9763
6–60 months (5 years)	$H_{x,y}$	<i>SPI</i>	0.8513	0.9493	0.9289
		<i>SDI</i>	0.8160	0.9216	0.8968
	$\Delta\alpha_{x,y}$	<i>SPI</i>	1.7909	1.9057	1.8655
		<i>SDI</i>	1.7778	1.9044	1.8580
6–120 months (10 years)	$H_{x,y}$	<i>SPI</i>	0.8465	0.8201	0.7974
		<i>SDI</i>	0.7564	0.7822	0.7614
	$\Delta\alpha_{x,y}$	<i>SPI</i>	1.9318	1.9587	1.9319
		<i>SDI</i>	1.8917	1.9447	1.9203
6–228 months (19 years)	$H_{x,y}$	<i>SPI</i>	0.8275	0.7513	0.7342
		<i>SDI</i>	0.7435	0.7360	0.7201
	$\Delta\alpha_{x,y}$	<i>SPI</i>	2.0109	1.9934	1.9712
		<i>SDI</i>	1.9630	1.9850	1.9663

Table 6 Hurst, PCC, and SRCC’s values concerning multifractal strength variations in the time series

		y series	x series		
			precipitation	T_{max}	T_{min}
$H_{x,y}$	SPI		0.7811	0.7555	0.7474
	SDI		0.7880	0.7422	0.7048
$P_{x,y}$	SPI		0.0604	0.0947	0.0139
	SDI		− 0.0341	− 0.0007	0.1116
$S_{x,y}$	SPI		0.0085	0.0575	− 0.0312
	SDI		− 0.0374	0.0015	0.1468

3.2 Results of Pearson, Spearman, Cross-Correlation, and Hurst’s values concerning multifractal strength variations in precipitation, temperature, and drought indices time series

The variations in multifractal strength in the time series were estimated (by MF-DFA) and analyzed by PCC, SRCC, cross-correlation, and MF-DXA; the results are sorted in Table 6 and Fig. 6. To analyze the multifractal strength variations in the time series (Precipitation, T_{max} , T_{min} , SPI, and SDI), the multifractality of each window was arranged sequentially to form a series (see Sect. 2.2) representing the multifractal strength fluctuations in each dataset.

The values of $P_{Pre, SPI}$, $P_{temp, SPI}$, and $P_{Tmin,SDI}$ were positive (Table 6). It was a proof of positive linear correlation between time series’ multifractal variations. The negative values of $P_{Pre, SDI}$ and $P_{Tmax, SDI}$ supported the notion that multifractal strength variations in precipitation and SDI, and T_{max} with SDI had negative (reverse) linear relationship. The results confirmed that as multifractal strength augments in precipitation and temperature time series, multifractal strength increases in meteorological drought. Likewise, augmentation of the multifractal strength in T_{min} increases the multifractality in hydrological drought. Conversely, multifractal strength augmentation in precipitation and T_{max} brings about a reduction in the multifractality of hydrological drought. Multifractal strength of meteorological drought exhibited more correlation with multifractal strength variations in precipitation and T_{max} , whereas hydrological drought multifractality displayed more correlation with multifractal strength variations in T_{min} . SPI and SDI presented the weakest linear relationship to T_{min} and T_{max} , respectively.

As shown in Table 5, the values of $S_{Pre,SPI}$, $S_{Tmax,SPI}$, $S_{Tmin,SDI}$, and $S_{Tmax,SDI}$ were positive while $S_{Tmin,SPI}$ and $S_{Pre,SDI}$ were negative, verifying a positive (direct) and a negative (reverse) monotonical relation between time series, respectively. $S_{Tmax,SPI}$ was higher than $S_{Tmax,SDI}$, indicating that the multifractal strength variations in the T_{max} time series and the SPI were more monotonically related than T_{max} and SDI. Higher values of $S_{Pre,SDI}$ and $S_{Tmin,SDI}$ in comparison with $S_{Pre,SPI}$ and $S_{Tmin,SPI}$ suggested the existence of a more substantial relationship between multifractality in precipitation and T_{min} with hydrological drought multifractality than meteorological drought. The results made clear that multifractality variations in meteorological and hydrological droughts exhibited noticeable monotonic relation with T_{max} and T_{min} , respectively. On the contrary, multifractality variations in meteorological and hydrological drought displayed negligible monotonic relationship with precipitation and T_{min} multifractal strength variations, respectively.

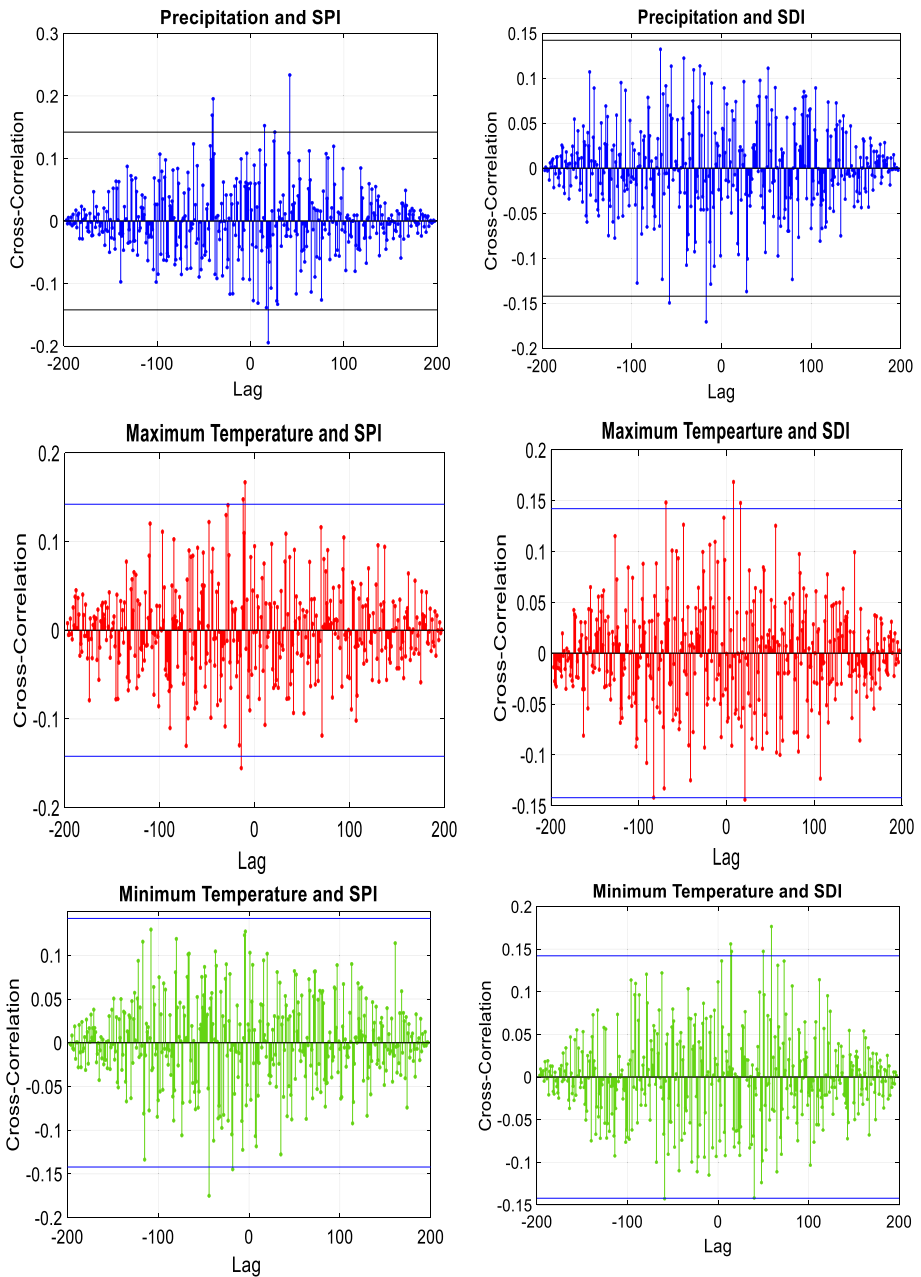


Fig. 6 The cross-correlation graphs concerning multifractal strength variations in precipitation and temperature time series and drought indices (the blue horizontal lines are confidence bounds consisting of 2 standard errors)

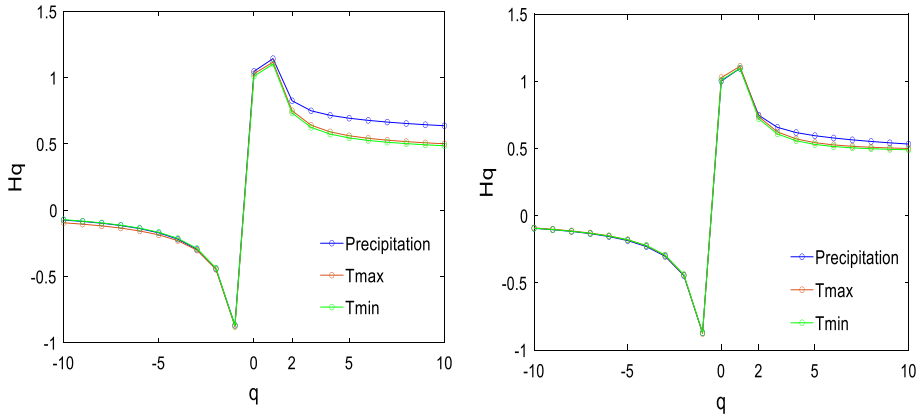


Fig. 7 The q -order Hurst exponent diagram ($H(q) \sim q$) concerning precipitation, T_{max} , and T_{min} and SPI (left) and SDI (right) time series

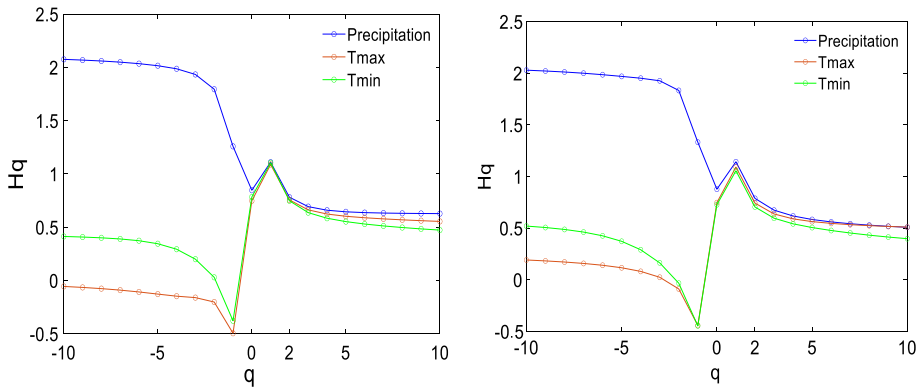


Fig. 8 The q -order Hurst exponent diagram ($H(q) \sim q$) concerning multifractal strength variations in precipitation, T_{max} , and T_{min} and SPI (left) and SDI (right) time series

According to Fig. 6, the highest cross-correlation was recorded between multifractal variations in precipitation and drought indices. Besides, the cross-correlation between multifractal variations in precipitation and SPI was more effective than precipitation and SDI. It implied that multifractal variations in meteorological and hydrological droughts were more sensitive to multifractal changes in precipitation than temperature. Moreover, multifractal fluctuations in precipitation more influenced multifractal variations in meteorological drought than hydrological drought.

A higher level of cross-correlation was recorded between multifractal variations of T_{max} and drought indices than T_{min} and drought indices. It proved that multifractal variations in drought indices were more sensitive to multifractal fluctuations in T_{max} than T_{min} . The maximum recorded cross-correlation value related to multifractal variations in temperature and SDI, providing evidence for high sensitivity of multifractal variations in hydrology drought (compared with meteorological drought) to multifractality in temperature.

The existence of the long-range persistence cross-correlation between multifractal strength variations in all time series was illustrated by the generalized Hurst exponent

values greater than 0.5 (Table 6). The highest value of generalized Hurst exponent was associated with precipitation, confirming the highest long-range persistent cross-correlation between precipitation and drought indices. The generalized Hurst exponent values confirmed the linear and sensitivity analysis results concerning the relationship between multifractal strength variations in the time series. It verified that there was a substantial connection between meteorological drought and precipitation.

The q -order Hurst exponent diagram ($H(q) \sim q$) was used to investigate the fractality of cross-correlation between time series (Figs. 7 and 8).

It is clear from Figs. 7 and 8 that cross-correlation between the time series exhibited multifractal properties due to the nonlinear dependence of $H(q)$ on q . The more nonlinear relationship between $H(q)$ and q , the greater the multifractal strength. Therefore, the cross-correlation between precipitation and drought indices (for original time series and multifractal strength variations in the time series) was more multifractal than temperature and drought indices. The multifractal analysis confirmed PCC, SRCC, and cross-correlation results concerning the quality of the relationship between precipitation and drought indices. The multifractal, PCC, SRCC, and cross-correlation results indicated that drought indices were highly sensitive to precipitation than temperature. Moreover, variations in droughts multifractality were more influenced by precipitation multifractality than temperature multifractality. Furthermore, meteorological drought and its multifractality were significantly impacted (sensitive and dependent) by precipitation and its multifractality, whereas hydrological drought and its multifractality were considerably affected by temperature and its multifractality.

According to mentioned results, we are able to draw a number of conclusions:

The linear correlation between precipitation and drought indices was stronger than temperature and drought indices. Meteorological drought had a significant linear and monotonic relationship with precipitation and T_{\min} , whereas hydrological drought had a considerable linear and monotonic relationship with T_{\max} . It was verified that cross-correlation between precipitation and drought indices was more long-range persistent than temperature and drought indices. Moreover, the cross-correlation between precipitation and meteorological drought had more long-term memory than precipitation and hydrological drought. Additionally, the cross-correlation between T_{\max} and drought indices exhibited more long-range persistency than T_{\min} and drought indices. The multifractal analysis confirmed correlation, monotonic, and sensitivity analysis results so that meteorological drought was sensitive to precipitation fluctuations and hydrological drought presented sensitivity to temperature variations.

The analysis results of multifractal strength variations demonstrated that meteorological drought multifractality had a strong linear correlation with multifractal strength variations in precipitation and T_{\max} , whereas hydrological drought multifractality had a substantial linear relationship with T_{\min} . The multifractal strength variations in T_{\max} and meteorological drought (SPI) were monotonically related. Likewise, the multifractal strength variations in hydrological drought (SDI) and precipitation and T_{\min} exhibited an influential monotonic relationship. The generalized Hurst exponent indicated that the cross-correlation between multifractal strength variations in all time series was long-range persistent. It was verified that as meteorological drought depended on precipitation and hydrological drought depended on temperature from linear correlation, monotonic relation, and cross-correlation points of view, multifractality in meteorological and hydrological droughts was dependent on multifractal variations in precipitation and temperature, respectively.

The analysis results of timescale changing proved augmentation of the long-range persistency of cross-correlation owing to the reduction in scale length. However, the

multifractal strength declined as a cutback in scale length except for the 6–24 months scale. At the 6–24 months scale, $\Delta\alpha_{Tmax,SPI}$, $\Delta\alpha_{Tmin,SPI}$, $\Delta\alpha_{Tmax,SDI}$, and $\Delta\alpha_{Tmin,SDI}$ experienced increments. The $\Delta\alpha$ positive values for all scale-lengths provided evidence for more probability of large local fluctuations than small local fluctuations in the time series.

The q -order Hurst exponent graph ($H(q) \sim q$) verified that cross-correlation between the time series exhibited multifractal properties, and the cross-correlation between precipitation and drought indices was more multifractal than temperature and drought indices. Since the multifractal strength of the cross-correlation between precipitation and droughts (meteorological and hydrological) was stronger than the multifractal strength of the cross-correlation between temperature and droughts, droughts' sensitivity to precipitation is less than temperature. In other words, it demonstrates the leading role of temperature on drought events. Multifractal analysis indicated that as there was a more substantial linear relation, monotonical correlation, and long-range persistency between precipitation and droughts than temperature and droughts, the cross-correlation between droughts and precipitation was more multifractal than droughts and temperature. The cross-correlation of multifractal strength variations between precipitation and droughts (meteorological and hydrological) was multifractal than temperature and droughts. This proved that multifractal strength variations in droughts are more affected by temperature than precipitation.

Several studies hitherto have been conducted on meteorological and hydrological drought association (Li et al. 2020, 2018; Liu et al. 2019a, b; Zhu et al. 2019; Yao et al. 2020), cross-correlation analysis of hydro-meteorological time series (Wei et al. 2020), and multifractal characterization of drought (Adarsh et al. 2019; Hou et al. 2018; Toluwalope Ogunjo 2021; Adarsh and Priya 2021); however, no research has been performed on the sensitivity of meteorological and hydrological drought to precipitation and temperature, besides meteorological and hydrological droughts' multifractality dependence on precipitation and temperature multifractality. Therefore, this issue was addressed in the present study to broaden our understanding of droughts mechanism.

4 Conclusion

It was attempted to evaluate meteorological and hydrological droughts' susceptibility to precipitation and temperature, besides meteorological and hydrological droughts' multifractality dependence on precipitation and temperature multifractality. The nonlinear dynamic and cross-correlation results indicated that precipitation had a greater effect on droughts (meteorological and hydrological) than temperature. In other words, droughts were more sensitive to precipitation fluctuations than temperature fluctuations. Concerning temperature, meteorological and hydrological droughts were dependent on the minimum and maximum temperatures, respectively. The relationship between precipitation and meteorological drought was more long-range persistence than precipitation and hydrologic drought. Besides, the correlation between maximum temperature and droughts was more long-range persistence than minimum temperature and droughts. Analysis of nonlinear dynamic patterns governing the systems proved that the multifractal strength of meteorological drought depended on the multifractal strength of precipitation and maximum temperature, whereas the multifractal strength of hydrological drought depended on the multifractal strength of the minimum temperature. The analysis results of timescale changing proved augmentation of the long-range persistency of cross-correlation owing to the reduction in scale length. However, the multifractal strength declined as a cutback in scale

length except for the 6–24 months scale. At the 6–24 months scale, $\Delta\alpha_{Tmax,SPI}$, $\Delta\alpha_{Tmin,SPI}$, $\Delta\alpha_{Tmax,SDI}$, and $\Delta\alpha_{Tmin,SDI}$ experienced increments. The $\Delta\alpha$ positive values for all scale-lengths provided evidence for more probability of large local fluctuations than small local fluctuations in the time series. The q-order Hurst exponent graph ($H(q) \sim q$) verified that cross-correlation between the time series exhibited multifractal properties, and the cross-correlation between precipitation and drought indices was more multifractal than temperature and drought indices, demonstrating the leading role of temperature on drought events.

This study had a few limitations, including it did not consider the underlying relationship between other parameters (such as wind speed, sunshine, and evapotranspiration) and droughts (meteorological and hydrological). Moreover, it did not examine the impact of other non-climatic (or human factors) elements such as land-use or -cover change on nonlinear dynamic patterns governing meteorological and hydrological droughts. However, this study suggested a novel approach for those interested in studying the nonlinear dynamic mechanisms governing droughts (meteorological and hydrological) and hydrological elements.

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Code availability Codes that support the findings of this study are available from the corresponding author upon reasonable request. The corresponding author is ready to share data with other researchers who send their request to this Email address: fattahi.mh@gmail.com.

Declarations

Conflicts of interest The authors have no conflict of interest to declare.

References

- Adarsh S, Priya KL (2021) Multifractal description of droughts in western India using detrended fluctuation analysis. Springer, Cham. https://doi.org/10.1007/978-3-030-59148-9_9
- Adarsh S, Kumar DN, Deepthi B, Gayathri G, Aswathy SS, Bhagyasree S (2019) Multifractal characterization of meteorological drought in India using detrended fluctuation analysis. *Int J Climatol* 39:4234–4255. <https://doi.org/10.1002/joc.6070>
- Adarsh S, Dharan DS, Nandhu AR, Vishnu BA, Mohan VK, Watorek M (2020) Multifractal description of streamflow and suspended sediment concentration data from Indian river basins. *Acta Geophys* 68:519–535. <https://doi.org/10.1007/s11600-020-00407-2>
- Agana NA, Homaifar A (2017) A deep learning based approach for long-term drought prediction. *South-eastCon 2017*. Concord, NC, pp. 1–8. DOI: <https://doi.org/10.1109/SECON.2017.7925314>

- Aghelpour P, Bahrami-Pichaghchi H, Kisi O (2020) Comparison of three different bio-inspired algorithms to improve ability of neuro fuzzy approach in prediction of agricultural drought, based on three different indexes. *Comput Electron Agric* 170:105279. <https://doi.org/10.1016/j.compag.2020.105279>
- Ahmed K, Shahid S, Nawaz N (2018) Impacts of climate variability and change on seasonal drought characteristics of Pakistan. *Atmos Res* 214:364–374. <https://doi.org/10.1016/j.atmosres.2018.08.020>
- An G, Hao Z (2017) Variation of precipitation and streamflow in the upper and middle Huaihe River Basin, China, from 1959–2009. *J Coast Res* 80:69–79. <https://doi.org/10.2112/SI80-010.1>
- Benesty J, Chen J, Huang Y, Cohen I (2009) Pearson correlation coefficient. In: *Noise reduction in speech processing*. Springer, Berlin. https://doi.org/10.1007/978-3-642-00296-0_5
- Bhardwaj K, Shah D, Aadhar S, Mishra V (2020) Propagation of meteorological to hydrological droughts in India. *J Geophys Res Atmos* 125(22):e2020JD033455. <https://doi.org/10.1029/2020JD033455>
- Byakatonda J, Parida BP, Moalafhi DB, Kenabatho PK (2018) Analysis of long-term drought severity characteristics and trends across semiarid Botswana using two drought indices. *Atmos Res* 213:492–508. <https://doi.org/10.1016/j.atmosres.2018.07.002>
- Cao G, Shi Y (2017) Simulation analysis of multifractal detrended methods based on the ARFIMA process. *Chaos Soliton Fract* 105:235–243. <https://doi.org/10.1016/j.chaos.2017.10.038>
- Chatterjee S, Ghosh D (2021) Impact of Global Warming on SENSEX fluctuations—A study based on Multifractal detrended cross correlation analysis between the temperature anomalies and the SENSEX fluctuations. *Phys A* 571:125815. <https://doi.org/10.1016/j.physa.2021.125815>
- Cleveland RB, Cleveland WS, McRae J, Terpenning I (1990) STL: A seasonal-trend decomposition procedure based on loess. *J off Stat* 6:3–73
- Crow WT, Kumar SV, Bolten JD (2012) On the utility of land surface models for agricultural drought monitoring. *Hydrol Earth Syst Sci* 16:3451–3460. <https://doi.org/10.5194/hess-16-3451-2012>
- Hao Z, Hao F, Sing VP, Ouyang W, Cheng H (2017a) An integrated package for drought monitoring, prediction and analysis to aid drought modeling and assessment. *Environ Model Softw* 91:199–209. <https://doi.org/10.1016/j.envsoft.2017.02.008>
- Hao Z, Yuan X, Xia Y, Hao F, Singh VP (2017b) An Overview of Drought Monitoring and Prediction Systems at Regional and Global Scales. *Bull Am Meteorol Soc* 98(9):1879–1896. <https://doi.org/10.1175/BAMS-D-15-00149.1>
- Hao Z, Singh VP, Xia Y (2018) Seasonal Drought Prediction: Advances, Challenges, and Future Prospects. *Rev Geophys* 56(1):108–141. <https://doi.org/10.1002/2016RG000549>
- Harisuseno D (2020) Meteorological drought and its relationship with southern oscillation index (SOI). *Civ Eng J* 6(10):1864–1875. <https://doi.org/10.28991/cej-2020-03091588>
- Hou W, Feng G, Yan P et al (2018) Multifractal analysis of the drought area in seven large regions of China from 1961 to 2012. *Meteorol Atmos Phys* 130:459–471. <https://doi.org/10.1007/s00703-017-0530-0>
- Kantelhardt JW, Zschiegner SA, Koscielny-Bunde E, Bunde A, Havlin S, Stanley HE (2002) Multifractal detrended fluctuation analysis of nonstationary time series. *Phys A* 316:87. [https://doi.org/10.1016/S0378-4371\(02\)01383-3](https://doi.org/10.1016/S0378-4371(02)01383-3)
- Kendon M, McCarthy M, Jevrejeva S, Matthews A, Sparks T, Garforth J (2020) State of the UK Climate 2019. *Int J Climatol* 40:1–69. <https://doi.org/10.1002/joc.6726>
- Li Q, Zeng M, Wang H, Li P, Wang K, Yu M (2015) Drought assessment using a multivariate drought index in the Huaihe River basin of Eastern China. *Proc Int as Hydrol Sci* 369:61–67. <https://doi.org/10.5194/piahs-369-61-2015>
- Li B, Zhu C, Liang Z, Wang G, Zhang Y (2018) Connections between meteorological and hydrological droughts in a semi-arid basin of the middle Yellow River. *Proc Int as Hydrol Sci* 379:403–407. <https://doi.org/10.5194/piahs-379-403-2018>
- Li Q, He P, He Y et al (2020) Investigation to the relation between meteorological drought and hydrological drought in the upper Shaying River Basin using wavelet analysis. *Atmos Res* 234:104743. <https://doi.org/10.1016/j.atmosres.2019.104743>
- Liu Y, Ren L, Singh VP, Yong B, Jiang S, Yuan F, Yang X (2019a) Understanding the Spatiotemporal Links Between Meteorological and Hydrological Droughts from a Three-Dimensional Perspective. *J Geophys Res Atmos* 124(6):3090–3109. <https://doi.org/10.1029/2018JD028947>
- Liu Y, Zhu Y, Ren L, Singh VP, Yong B, Jiang S, Yuan F, Yang X (2019b) Understanding the Spatiotemporal Links Between Meteorological and Hydrological Droughts from a Three-Dimensional Perspective. *J Geophys Res Atmos* 124(6):3090–3109. <https://doi.org/10.1029/2018JD028947>
- Livina V, Kizner Z, Braun P, Molnar T, Bunde A, Havlin S (2007) Temporal scaling comparison of real hydrological data and model runoff records. *J Hydrol* 336(1–2):186–198. <https://doi.org/10.1016/j.jhydrol.2007.01.014>
- Lyerly SB (1952) The average spearman rank correlation coefficient. *Psychometrika* 17:421–428. <https://doi.org/10.1007/BF02288917>

- Malik A, Kumar A, Singh RP (2019) RP Application of heuristic approaches for prediction of hydrological drought using multi-scalar streamflow drought index. *Water Resour Manage* 33:3985–4006. <https://doi.org/10.1007/s11269-019-02350-4>
- Manimaran P, Narayana AC (2018) Multifractal detrended cross-correlation analysis on air pollutants of University of Hyderabad Campus, India. *Phys A* 502:228–235. <https://doi.org/10.1016/j.physa.2018.02.160>
- McKee TB, Doesken NJ, Kleist J (1993) The relationship of drought frequency and duration to time scales. *Proceedings of the Eighth Conference on Applied Climatology*, American Meteorological Society 179–184.
- Miloš LR, Hačigan C, Miloš MC, Barna FM, Božić C (2020) Multifractal detrended fluctuation analysis (MF-DFA) of stock market indexes empirical evidence from seven central and eastern european markets. *Sustainability* 12(2):535. <https://doi.org/10.3390/su12020535>
- Morales Martínez JL, Segovia-Domínguez I, Quiros Rodríguez I, Horta-Rangel FA, Sosa-Gómez G (2021) A modified Multifractal detrended fluctuation analysis (MFDFA) approach for multifractal analysis of precipitation. *Phys A* 565:125611. <https://doi.org/10.1016/j.physa.2020.125611>
- Nabipour N, Dehghani M, Mosavi A, Shamshirband S (2020) Short-term hydrological drought forecasting based on different nature-inspired optimization algorithms hybridized with artificial neural networks. *IEEE Access* 8:15210–15222. <https://doi.org/10.1109/ACCESS.2020.2964584>
- Nalbantis I, Tsakiris G (2009) Assessment of hydrological drought revisited. *Water Resour Manage* 23:881–897. <https://doi.org/10.1007/s11269-008-9305-1>
- Ozkaya A, Zerberg Y (2019) A 40-Year analysis of the hydrological drought index for the tigris basin. *Turkey Water* 11:657. <https://doi.org/10.3390/w11040657>
- Peña-Gallardo M, Vicente-Serrano SM, Hannaford J et al (2019a) Complex influences of meteorological drought time-scales on hydrological droughts in natural basins of the contiguous United States. *J Hydrol* 568:611–625. <https://doi.org/10.1016/j.jhydrol.2018.11.026>
- Peña-Gallardo M, Vicente-Serrano SM, Hannaford J, Lorenzo-Lacruz J, Svoboda M, Domínguez Castro F, Maneta M, Tomas-Burguera M, El Kenawy A (2019b) Complex influences of meteorological drought time-scales on hydrological droughts in natural basins of the contiguous United States. *J Hydrol* 568:611–625. <https://doi.org/10.1016/j.jhydrol.2018.11.026>
- Rahmani F, Fattahi MH (2021) Phase space mapping of pivotal climatic and non-climatic elements affecting basin' drought. *Arab J Geosci* 14:397. <https://doi.org/10.1007/s12517-021-06734-y>
- Santos da Silva H, Rodrigo Santos Silva J, Stosic T (2020) Multifractal analysis of air temperature in Brazil. *Phys A* 549:124333. <https://doi.org/10.1016/j.physa.2020.124333>
- Stefan S, Ghioca M, Rambu N, Boroneant C (2004) Study of meteorological and hydrological drought in southern Romania from observational data. *Int J Climatol* 24(7):871–881. <https://doi.org/10.1002/joc.1039>
- Sun X, Chen H, Wu Z, Yuan Y (2001) Multifractal analysis of hang seng index in hong kong stock market. *Phys A* 291(1–4):553–562. [https://doi.org/10.1016/S0378-4371\(00\)00606-3](https://doi.org/10.1016/S0378-4371(00)00606-3)
- Tatli H, Dalfes HN (2020) Long-time memory in drought via detrended fluctuation analysis. *Water Resour Manage* 34:1199–1212. <https://doi.org/10.1007/s11269-020-02493-9>
- Tatli H, Menteş ŞS (2019) Detrended cross-correlation patterns between North Atlantic oscillation and precipitation. *Theor Appl Climatol* 138:387–397. <https://doi.org/10.1007/s00704-019-02827-7>
- Tian Y, Xu Y, Wang G (2018) Agricultural drought prediction using climate indices based on Support Vector Regression in Xiangjiang River basin. *Sci Total Environ* 622–623:710–720. <https://doi.org/10.1016/j.scitotenv.2017.12.025>
- Tigkas D (2008) Drought characterization and monitoring in regions of Greece. *Eur Water* 23:29–39
- Tigkas D, Vangelis H, Tsakiris G (2015) DrinC: a software for drought analysis based on drought indices. *Earth Sci Inform* 8(3):697–709. <https://doi.org/10.1007/s12145-014-0178-y>
- Toluwalope Ogunjo S (2021) Multifractal properties of meteorological drought at different time scales in a tropical location. *Fluct Noise Lett* 20(1):2150007. <https://doi.org/10.1142/S0219477521500073>
- Toluwalope Ogunjo S, Fuwape I, Rabiu AB (2021) Samuel Oluyamo S (2021) Multifractal analysis of air and soil temperatures. *Chaos* 31:033110. <https://doi.org/10.1063/5.0029658>
- Tzanis CG, Koutsogiannis I, Philippopoulos K, Kalamaras N (2020) Multifractal detrended cross-correlation analysis of global methane and temperature. *Remote Sens* 12(3):557. <https://doi.org/10.3390/rs12030557>
- Uddin MJ, Hu J, Islam ARMT, Eibek KU, Nasrin ZM (2020) A comprehensive statistical assessment of drought indices to monitor drought status in Bangladesh. *Arab J Geosci* 13:323. <https://doi.org/10.1007/s12517-020-05302-0>

- Ullah I, Ma X, Yin J, Asfaw TG, Azam K, Syed S, Liu M, Arshad M, Shahzaman M (2021) Evaluating the meteorological drought characteristics over Pakistan using in situ observations and reanalysis products. *Int J Climatol*. <https://doi.org/10.1002/joc.7063>
- Van Loon AF, Laaha G (2015) Hydrological drought severity explained by climate and catchment characteristics. *J Hydrol* 526:3–14. <https://doi.org/10.1016/j.jhydrol.2014.10.059>
- Wang B, Wei Y, Xing Y, Ding W (2019) Multifractal detrended cross-correlation analysis and frequency dynamics of connectedness for energy futures markets. *Phys A* 527:121194. <https://doi.org/10.1016/j.physa.2019.121194>
- Wei X, Zhang H, Gong X, Wei X, Dang C, Zhi T (2020) Intrinsic cross-correlation analysis of hydro-meteorological data in the Loess Plateau, China. *Int J Environ Res Public Health* 17:2410. <https://doi.org/10.3390/ijerph17072410>
- Wu Y, He Y, Wu M et al (2018) Multifractality and cross-correlation analysis of streamflow and sediment fluctuation at the apex of the Pearl River Delta. *Sci Rep* 8:16553. <https://doi.org/10.1038/s41598-018-35032-z>
- Wu L, Wang M, Zhao T (2020) Joint multifractal analysis and source testing of river level records based on multifractal detrended cross-correlation analysis. *Complexity*. <https://doi.org/10.1155/2020/1532805>
- Xie C, Zhou Y, Wang G, Yan X (2017) Analyzing the cross-correlation between onshore and offshore RMB exchange rates based on multifractal detrended cross-correlation analysis (MF-DCCA). *Fluct Noise Lett* 16(1):1750004. <https://doi.org/10.1142/S0219477517500043>
- Xu L, Chen N, Zhang Z, Chen Z (2018) An evaluation of statistical, NMME and hybrid models for drought prediction in China. *J Hydrol* 566:235–249. <https://doi.org/10.1016/j.jhydrol.2018.09.020>
- Yang Y, McVicar TR, Donohue RJ, Zhang Y, Roderick ML, Chiew FHS, Zhang L, Zhang J (2017) Lags in hydrologic recovery following an extreme drought: assessing the roles of climate and catchment characteristics. *Water Resour Res* 53(6):4821–4837. <https://doi.org/10.1002/2017WR020683>
- Yao N, Zhao H, Li Y, Biswas A, Feng H, Liu F, Pulatov B (2020) National-scale variation and propagation characteristics of meteorological, agricultural, and hydrological droughts in China. *Remote Sens* 12(20):3407. <https://doi.org/10.3390/rs12203407>
- Yu MX, Liu XL, Wei L, Li QF, Zhang JY, Wang GQ (2016) Drought Assessment by a Short-/Long-Term Compositing Drought Index in the Upper Huaihe River Basin, China. *Adv. Meteorol.* 1–10. [Artn798656810.1155/2016/7986568](https://doi.org/10.1155/2016/7986568)
- Zareei AR, Shabani A, Mahmoudi MR (2021) Susceptibility assessment of winter wheat, barley and rapeseed to drought using generalized estimating equations and cross-correlation function. *Environ Process* 8:163–197. <https://doi.org/10.1007/s40710-021-00496-1>
- Zhang W, Wang P, Li X, Shen D (2018) Multifractal detrended cross-correlation analysis of the return-volume relationship of bitcoin market. *Complexity*. <https://doi.org/10.1155/2018/8691420>
- Zhang L, Li H, Liu D et al (2021) Application of an improved multifractal detrended fluctuation analysis approach for estimation of the complexity of daily precipitation. *Int J Climatol*. <https://doi.org/10.1002/joc.7092>
- Zhao A, Zhang A, Cao S, Liu X, Liu J, Cheng D (2018) Responses of vegetation productivity to multi-scale drought in Loess Plateau, China. *CATENA* 163:165–171. <https://doi.org/10.1016/j.catena.2017.12.016>
- Zhou WX (2008) Multifractal detrended cross-correlation analysis for two non-stationary signals. *Phys Rev E* 77:066211. <https://doi.org/10.1103/PhysRevE.77.066211>
- Zhu Y, Liu Y, Wang W, Singh VP, Ma X, Yu Z (2019) Three-dimensional characterization of meteorological and hydrological droughts and their probabilistic links. *J Hydrol* 578:124016. <https://doi.org/10.1016/j.jhydrol.2019.124016>
- Zou S, Zhang T (2020) Multifractal detrended cross-correlation analysis of the relation between price and volume in European carbon futures markets. *Phys A* 537:122310. <https://doi.org/10.1016/j.physa.2019.122310>