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CROSS-CORRELATIONS BETWEEN BACTERIAL FOODBORNE DISEASES AND METEOROLOGICAL FACTORS BASED ON MF-DCCA: A CASE IN SOUTH KOREA

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Abstract

In this study, we apply multifractal detrended cross-correlation analysis (MF-DCCA) to examine the nonlinear cross-correlations between bacterial foodborne diseases (FBDs) and meteorological factors in South Korea. The results demonstrate that power-law cross-correlations between bacterial FBD and meteorological factors exist; and that multifractal characteristics are significant. In addition, the cross-correlation between bacterial FBD and temperature is more persistent than that between bacterial FBD and humidity. Comparison of the strengths of multifractal spectra showed that the degree of multifractality of the Humidity/FBD time series pair is greater than that of Temperature/FBD pair; this indicates that the monthly number of outpatient FBD cases is more sensitive to humidity. Furthermore, to document the major

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source of multifractality, we shuffle the original series. We conclude that both the long-range correlations and fat-tail distribution contribute to the multifractality of the Temperature/FBD time series pair. The long-range correlations are also an important source that contributes to the multifractality between bacterial FBD and humidity time series.

Keywords: Multifractality; Cross-Correlation; Bacterial Foodborne Diseases; Meteorological Factors.

1. INTRODUCTION

The influence of climate change on biophysics is complex, not only it can affect plants and the production of grain and crops, but evidence has shown that climate change can cause diseases and other adverse effects on human health. Previous studies have shown that climate change has had a significant impact on food safety,[1–5] which is particularly reflected in the correlations between climate change and bacterial foodborne disease (FBD). In Ref. 6, the authors investigated the relationship between temperature and salmonella infections. Craig *et al.*[7] observed the associations between environmental changes and vibrio infections and pointed out that warming patterns coincided with the emergence of vibriosis in northern Europe.

Recently, Park *et al.*[8] investigated the impact of eight climatic variables on the incidence of bacterial FBD in South Korea and found that combinations of climate factors such as relative humidity, temperature, insolation, cloudiness, and precipitation are significantly associated with FBD incidence.

However, few studies have focused on the cross-correlations between bacterial FBD and meteorological factors based on multifractal detrended cross-correlation analysis (MF-DCCA). It is well known that the multifractal detrended fluctuation analysis (MF-DFA) model can reveal the multifractal properties hidden in nonstationary time series.[9–16] The MF-DFA model has been used to analyze the multifractality of the signal series. However, to study the multifractal characteristics of two cross-correlated nonstationary time series, MF-DCCA is an effective method. MF-DCCA was first presented by Zhou.[17] Since then, it has been widely studied in various fields such as financial markets,[18,19] traffic flow,[20] geophysical data,[21] and vehicles and passengers.[22] In the field of climate change and meteorological factors, Zhang *et al.*[23] used MF-DCCA to analyze the cross-correlations between $PM_{2.5}$ and meteorological factors. The correlations between meteorological factors and agricultural futures markets were investigated by Cao *et al.*[24] using DCCA. Horvatic *et al.*[25] applied meteorological data to demonstrate the power-law cross-correlations between different simultaneously recorded time series.

Although many scholars have applied MF-DCCA for investigating the cross-correlations of meteorological factor series, the MF-DCCA model has hardly been applied to research on bacterial FBD. In this research, we focus on the cross-correlations between bacterial FBD and meteorological factors in South Korea. We first use the DCCA coefficient to check the cross-correlations between series and then adopt a cross-correlation test function to confirm whether cross-correlations exist for both Temperature/FBD and Humidity/FBD series pairs by comparing the critical values with the $\mathcal{X}^2(m)$ distribution. Subsequently, we use MF-DCCA to investigate the cross-correlations quantitatively. We examine the sources of the multifractal properties of both time series pairs. In prediction modeling for future patterns of diseases based on climate change, we believe that empirical research on the investigation of cross-correlations between bacterial FBD incidence and meteorological factors can be valuable.

The paper is organized as follows. In Sec. 2, we introduce the multifractal spectrum and MF-DCCA. In Sec. 3, we describe the data. We present empirical results in Sec. 4, while Sec. 5 concludes.

2. PRINCIPLES AND METHODOLOGY

2.1. Cross-Correlation Test Function

Assuming the existence of two time series, x_t and y_t, $t = 1, 2, \ldots, N$, the cross-correlation test function[26] is defined by

$$C_i = \frac{\sum_{k=i+1}^{N} x_k y_{k-i}}{\sqrt{\sum_{k=1}^{N} x_k^2 \sum_{k=1}^{N} y_k^2}}. \quad (1)$$

Then, we get the test statistic as follows:

$$Q_{cc}(m) = N^2 \sum_{i=1}^{m} \frac{C_i^2}{N-i}, \quad (2)$$

where m is the degrees of freedom. The distribution characteristics of the cross-correlation statistic $Q_{cc}(m)$ are close to that of the chi-square distribution with m degrees of freedom. We consider the cross-correlations between two time series as significant if the cross-correlation statistic exceeds the critical value of $\mathcal{X}^2(m)$. Otherwise, there are no cross-correlations between the two series.

2.2. Multifractal Detrended Cross-Correlation Analysis

Kantelhardt[9] proposed the MF-DFA method, which can effectively determine whether a time series has multifractal properties. To quantify the correlations between two nonstationary time series, Podobnik *et al.*[27] proposed the DCCA method, which was extended from DFA. Based on MF-DFA and DCCA, the MF-DCCA method was proposed to reveal the multifractal characteristics of two nonstationary time series by Zhou.[17] In this study, we adopt MF-DCCA to investigate the dynamic cross-correlations between bacterial FBD and meteorological factors. The general MF-DCCA procedure can be conducted by the following steps.

(1) The MF-DFA method based on random walk theory[28] has a time series summation process to avoid the instability of artificially-induced time series. Thus, for time series $\{x_t, t = 1, 2, \ldots, N\}$ and $\{y_t, t = 1, 2, \ldots, N\}$ of length N, construct the following summation sequence which removes the mean.

$$X(t) = \sum_{m=1}^{t} (x_m - \bar{x}), \quad t = 1, 2, \ldots, N, \quad (3)$$

$$Y(t) = \sum_{m=1}^{t} (y_m - \bar{y}), \quad t = 1, 2, \ldots, N, \quad (4)$$

where $\bar{x} = \frac{1}{N}\sum_{t=1}^{N} x_t$ and $\bar{y} = \frac{1}{N}\sum_{t=1}^{N} y_t$.

(2) Divide the new sequences X and Y into N_s non-overlapping segments with equal scale s, i.e. change the time scale. Therefore, the number of segments for the two series is $N_s = [N/s]$. In order to ensure that the series X and Y information are not lost during the division process, the same processes are repeated at the end of the two series. Thus, $2N_s$ segments are obtained for each series.

(3) Use the least squares method to fit s points in each subsegment $v, (v = 1, 2, \ldots, 2N_s)$, to obtain the fitting polynomial with k order in each segment as

$$x_v(i) = a_1 i^k + a_2 i^{k-1} + \cdots + a_k i + a_{k+1}, \quad i = 1, 2, \ldots, s, \quad (5)$$

$$y_v(i) = b_1 i^k + b_2 i^{k-1} + \cdots + b_k i + b_{k+1}, \quad i = 1, 2, \ldots, s. \quad (6)$$

(4) Calculate the covariance $F^2(s, v)$. When $v = 1, 2, \ldots, N_s$,

$$F^2(s, v) = \frac{1}{s} \sum_{i=1}^{s} \{|X[(v-1)s + i] - x_v(i)||Y[(v-1)s + i] - y_v(i)|\}. \quad (7)$$

When $v = N_s + 1, N_s + 2, \ldots, 2N_s$,

$$F^2(s, v) = \frac{1}{s} \sum_{i=1}^{s} \{|X[N - (v - N_s)s + i] - x_v(i)||Y[N - (v - N_s)s + i] - y_v(i)|\}. \quad (8)$$

(5) Calculate the mean of $2N_s$ segments, and obtain the q order wave function $F_q(s)$ as

$$F_q(s) = \left\{ \frac{1}{2N_s} \sum_{v=1}^{2N_s} [F^2(s, v)]^{\frac{q}{2}} \right\}^{\frac{1}{q}}. \quad (9)$$

When $q = 0$, according to Lopida's law,

$$F_q(s) = \exp\left\{ \frac{1}{2N_s} \sum_{v=1}^{2N_s} \ln[F^2(s, v)] \right\}. \quad (10)$$

$F_q(s)$ is a function of segment s and fractal order q. With the increase of s, the series are correlated by long-range power-law, and the generalized Hurst exponent $h_{xy}(q)$ is defined by $F_q(s) \propto s^{h_{xy}(q)}$. The range of $h_{xy}(q)$ indicates the extent to which the series is multifractal. A larger $\Delta H_{xy} = h_{xy}(q_{\min}) - h_{xy}(q_{\max})$ means stronger multifractal feature. $h_{xy}(q)$ represents the scaling behaviors of the segments with different q, they reveal the large and small fluctuations with $q > 0$ and $q < 0$, respectively. If $q = 2$, then MF-DCCA reduces to the standard DCCA, and the value of h_{xy} stays in the interval from 0 to 1. If $h_{xy}(2) = 0.5$, then the two time series are not cross-correlated and have no influence on each other. When $0.5 < h_{xy}(2) \leq 1$, the correlations between the two time series are persistent. When $h_{xy}(2) < 0.5$, the correlations between the two time series are antipersistent.[29] When the two time series are the same, the MF-DCCA reduces to MF-DFA.

Multifractal natures can also be described by the scaling exponent $\tau_{xy}(q)$ and multifractality spectrum $f_{xy}(\alpha)$. The scaling exponent $\tau_{xy}(q)$ is determined as

$$\tau_{xy}(q) = qh_{xy}(q) - 1. \tag{11}$$

The singularity strength α_{xy} and singularity spectrum $f_{xy}(\alpha)$ can be obtained via Legendre transform of $\tau_{xy}(q)$ as

$$\alpha = h_{xy}(q) + qh'_{xy}(q), \tag{12}$$

$$f_{xy}(\alpha) = q[\alpha_{xy} - h_{xy}(q)] + 1, \tag{13}$$

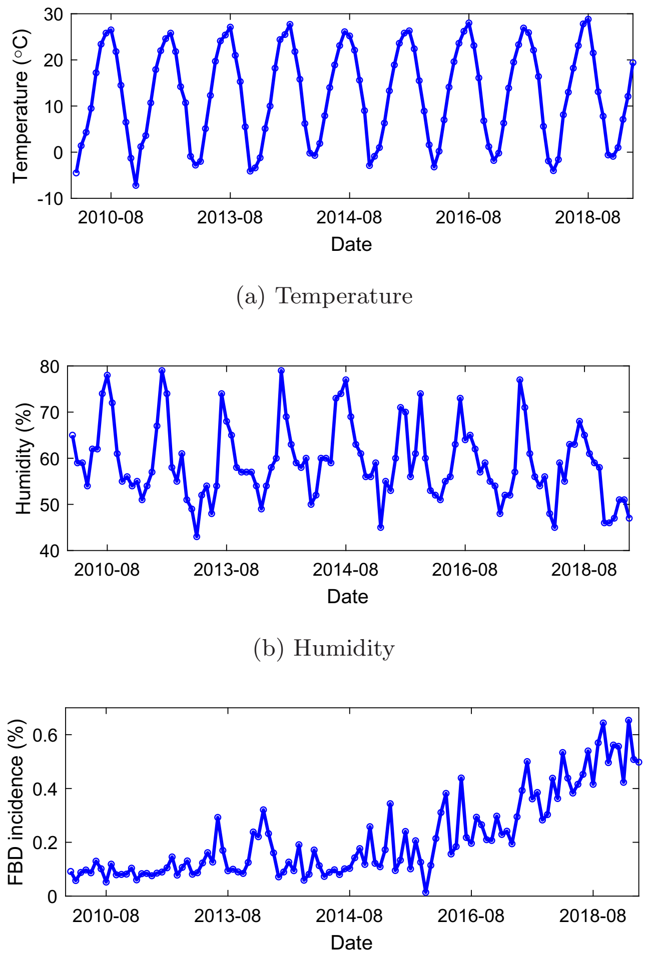
where α_{xy} is the singularity strength. The interval $\Delta\alpha_{xy} = \alpha_{xy_{\max}} - \alpha_{xy_{\min}}$ represents the degree of multifractality.[30] The larger α_{xy} represents stronger multifractality, which indicates that the cross-correlations between two series are greater. $f_{xy}(\alpha)$ is the singularity spectrum used to describe the fractal dimension of singularity strength α_{xy}.

3. DATA COLLECTION

We adopted monthly outpatient quantity data on bacterial FBD, mean temperature data, and relative humidity data in South Korea to investigate the cross-correlations between bacterial FBD and meteorological factors. The experimental sample for bacterial FBD was obtained from the "Health Insurance Review and Assessment Service". The samples for temperature (°C) and humidity (%) were obtained from the "Seoul Meteorological Administration". For more details, please refer to http://www.hira.or.kr/main.do and https://web.kma.go.kr/info_open/public_data/request.jsp. We used the calculated mean values of bacterial FBD and meteorological factors for each month from January 2010 to May 2019. Thus, each time series consisted of 113 data observations. The time series charts for the changing trends in temperature, humidity, and bacterial FBD incidence are shown in Fig. 1.

4. EXPERIMENT RESULTS

In this section, we first selected the appropriate parameters for the empirical model, and then conducted preliminary tests on the multifractality of two separate time series. After then, we apply the



(a) Temperature

(b) Humidity

(c) FBD incidence

Fig. 1 Time series of (a) temperature (b) humidity and (c) FBD incidence.

DCCA coefficient and cross-correlation test function to test the cross-correlations between bacterial FBD and meteorological factors. Moreover, we use the MF-DCCA to further investigate the cross-correlations. At last, we show the main sources of multifractality for each time series pair.

4.1. Parameter Selection

The appropriateness of parameter selection is important for the MF-DCCA model. These parameters include segment scale s, fractal order q, and order k, which are used to fit polynomials in Eq. (6). Generally, when fitting polynomials, linear, quadratic, cubic, or higher orders can be used. According to Ref. 31, the chosen k should be between 1 and 3. After comparing the multifractal spectrum with different k values, we chose $k = 2$ for the MF-DCCA model to prevent underfitting or overfitting of polynomials. According to Refs. 9, 19 and 31, the minimum segment size should be much larger than the polynomial order k. Thus, we set the minimum segment and maximum segment scale as $s_{\min} = 10$ and $s_{\max} = 20$, respectively; the total segment size is 11. Lashermes *et al.*[32] observed that the fractal orders q taken from -10 to 10 are sufficient in most cases. We took the total number of q by 21, from the interval between -10 and $+10$, that is, the interval was divided into 20 equal parts. Then, these parameters were taken into the MF-DCCA model for empirical research.

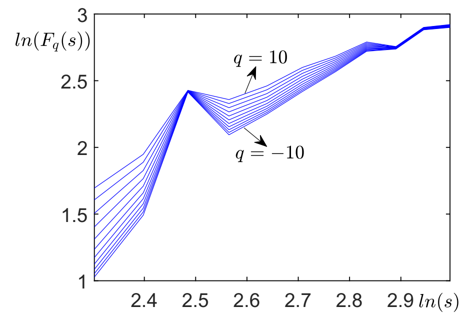
4.2. Preliminary Test on Multifractality

Previous studies have proved that temperature and humidity time series possess multifractal characteristics.[33–35] Therefore, before analyzing the cross-correlations between bacterial FBD and meteorological time series, we first applied MF-DFA to investigate the multifractality of temperature and humidity time series. Figure 2 shows the double log plots of $F_q(s)$ versus fractal order q and scale s for the temperature and humidity time series. For the two indices, the fluctuations increased with s, which implies the existence of power-law behavior and long-range correlations in each series. The decreasing slope with increasing q indicates that both the time series have multifractal characteristics.

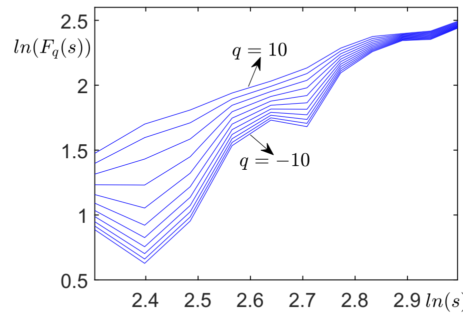
To measure the multifractality quantitatively, we estimated the properties of temperature and humidity. We computed the generalized Hurst exponent $h(q)$, and then obtained the scaling exponent $\tau(q)$ and singularity spectrum $f(\alpha)$.

Figure 3 shows that the generalized Hurst exponents for the two time series are not fixed values. $h(q)$ decreased with the increase of q, which indicates that the time series of temperature and humidity have multifractal properties. We observed that when $q = 2$, the parameters $h(2)$ calculated for all indices are greater than 0.5 (see Table 1); this means that small and large fluctuations have significant persistence. For the two time series, when q is less than 0, the value of $h(q)$ decreased rapidly with the increase in q, which shows that wavelet fluctuations have significant persistence. On the other hand, when $q > 0$, with the increasing q, $h(q)$ stayed low, indicating the minimum sustainability of large fluctuations. From the Hurst exponential curve, we define the degree of multifractality by equation

$$\Delta H(q) = h(q_{\min}) - h(q_{\max}). \quad (14)$$



(a) Temperature



(b) Humidity

Fig. 2 Log–log plots of fluctuation function $F_q(s)$ of (a) temperature and (b) humidity.

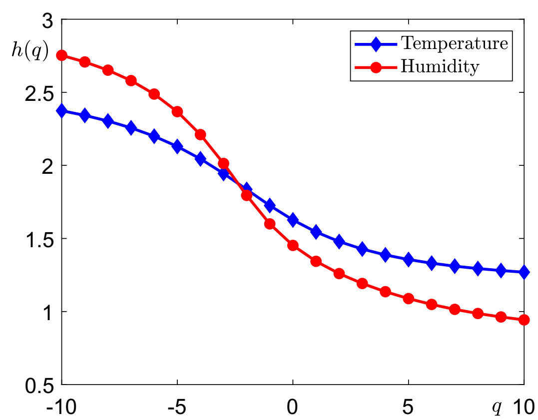


Fig. 3 Hurst exponent of temperature and humidity.

We calculated ΔH for each time series and listed the values related to multifractality in Table 1.

The multifractality of time series also can be analyzed by the scaling exponent curve and multifractal spectrum. We calculated $\tau(q)$ using Eq. (11). Figure 4 shows the scaling exponents of the two indices. A previous study[36] showed that the curvature of the scaling exponent can be used to measure multifractality. If a time series has stronger multifractality, then the curvature of the scaling

Table 1 Multifractality for temperature and humidity.

	$h(2)$	$\Delta H(q)$	$\Delta\alpha$
Temperature	1.4788	1.1049	1.5152
Humidity	1.2596	1.8100	2.4415

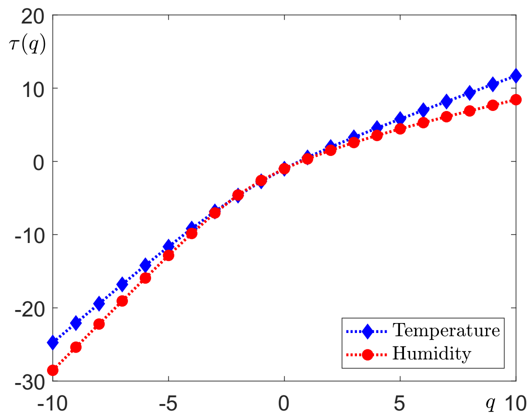


Fig. 4 Scaling exponent curve of temperature and humidity.

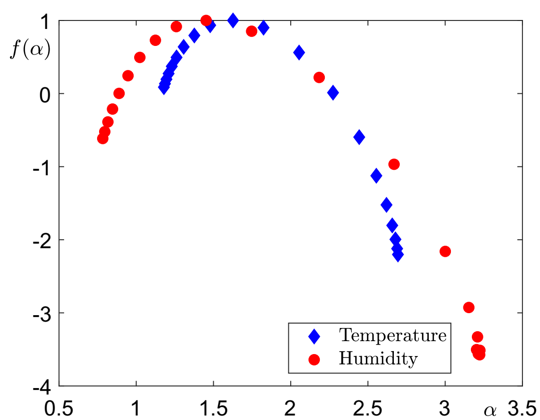


Fig. 5 Multifractal spectrum of temperature and humidity.

exponent curve is larger. A straighter line represents greater linearity.

Then, we calculated the singularity strength α and singularity spectrum $f(\alpha)$ using Eq. (13). As shown in Fig. 5, the width of the curve on the α-axis represents the degree of multifractal. A higher $\Delta\alpha$ indicates that the time series has a stronger multifractal property. From Fig. 5, the $\Delta H(q)$ and $\Delta\alpha$ of humidity are larger, which is consistent with the Hurst exponent and scaling exponent.

4.3. DCCA Coefficient

Before the testing of MF-DCCA, it is significant to verify the correlations between the FBD and meteorological factor time series. An efficient measure is the DCCA coefficient proposed by Zebende.[37] When dealing with highly nonstationary processes, the metric has proved to be effective in testing the cross-correlations between series.[38] The DCCA coefficient function is generally defined as follows:

$$\rho_{\mathrm{DCCA}} = \frac{F_{\mathrm{DCCA}}{}^2_{ab}(s)}{F_{\mathrm{DFA}a}(s)F_{\mathrm{DFA}b}(s)}. \tag{15}$$

$F_{\mathrm{DCCA}}{}^2_{ab}(s)$ is the fluctuation function of the detrended covariance of the time series pair; $F_{\mathrm{DFA}a}(s)$ and $F_{\mathrm{DFA}b}(s)$ are the detrended fluctuation functions of the corresponding single time series.

The values interval of ρ_{DCCA} ranged between -1 and 1. If $\rho_{\mathrm{DCCA}} = 1$, then the series pair is highly cross-correlated. If $\rho_{\mathrm{DCCA}} = 0$, then there is no cross-correlation. If ρ_{DCCA} is close to -1, then the cross-correlation of the series pair is more antipersistent. We depict the DCCA coefficient versus segment size s which ranged from 10 to 20 in Fig. 6.

All values are within the 0 to 1 interval, indicating the existence of cross-correlations between Temperature/FBD (rhombus) and Humidity/FBD (circle).

4.4. Cross-Correlation Test

In this section, we further verify the correlations between bacterial FBD and meteorological time series. With the degrees of freedom m ranging from 1 to 110, Eqs. (1) and (2) were selected to calculate the cross-correlation statistic $Q_{cc}(m)$ for the

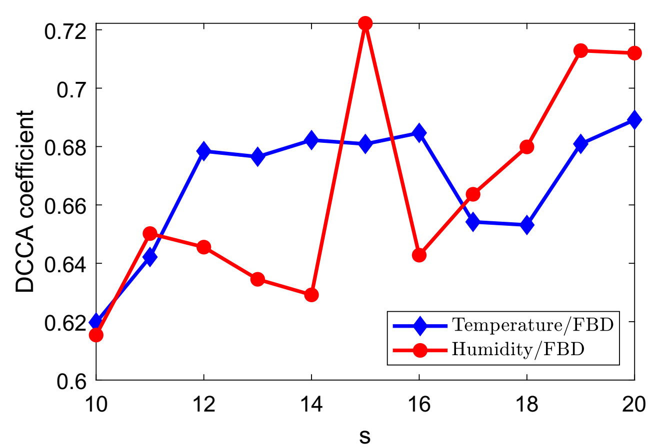


Fig. 6 DCCA coefficients for two time series pairs.

two time series. With m degrees of freedom, $Q_{\rm cc}(m)$ is approximately $\mathcal{X}^2(m)$ distributed. If the statistic $Q_{\rm cc}(m)$ exceeds the critical value of the $\mathcal{X}^2(m)$ distribution, then the cross-correlation is significant; otherwise, there is no cross-correlation between the two time series. In this study, we use the critical values for $\mathcal{X}^2(m)$ distribution at 5% level of significance.

Figure 7 shows the cross-correlation statistics for the two time series pairs of indices (Temperature/FBD and Humidity/FBD). The $Q_{\rm cc}(m)$ for the time series pairs is always greater than the critical values for the $\mathcal{X}^2(m)$ distribution, which implies statistically significant long-range cross-correlations between bacterial FBD and the two meteorological time series. In Fig. 7, the straight line represents the critical value of $\mathcal{X}^2(m)$ distribution while the dotted lines represent the cross-correlation statistic $Q_{\rm cc}(m)$ of the Temperature/FBD (uniform) and Humidity/FBD (nonuniform) pairs, respectively.

4.5. MF-DCCA Analysis

Because $\rho_{\rm DCCA}$ and $Q_{\rm cc}(m)$ show the existence of cross-correlations between the two time series pairs, to measure the cross-correlations quantitatively, we applied MF-DCCA to estimate the cross-correlations between Temperature/FBD and Humidity/FBD. In the first step, we depicted the double log plots of the $F_q(s)$ versus order q and scale s. Figure 8 presents the shape of fluctuation function for both series pairs. We note that for both Temperature/FBD and Humidity/FBD pairs, the fluctuation value increased linearly with time scale s, which indicates the existence of power-law behavior and long-range correlations in each series pair.

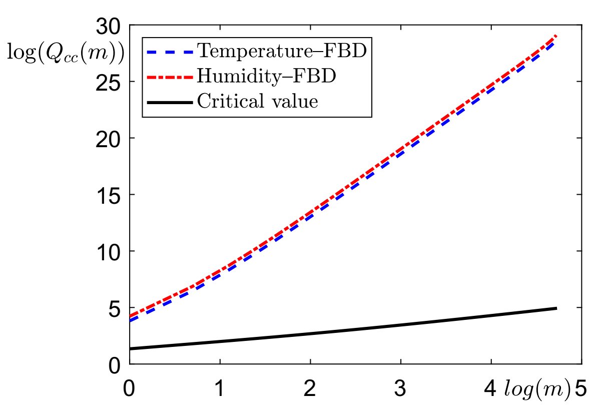
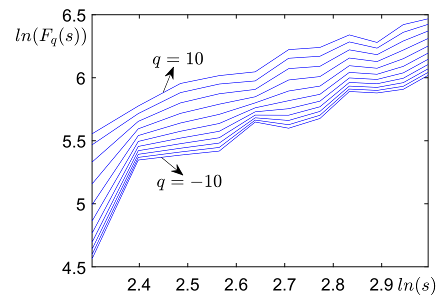
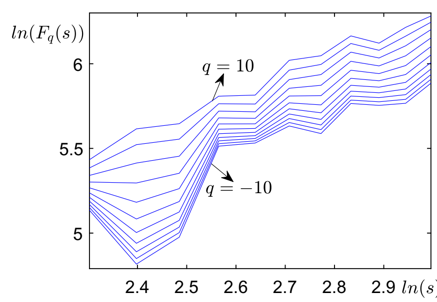


Fig. 7 Cross-correlation test versus log(m).



(a) Temperature/FBD



(b) Humidity/FBD

Fig. 8 Log–log plots of fluctuation function $F_q(s)$ of (a) Temperature/FBD and (b) Humidity/FBD.

The decreasing slope with increasing q implies that both time series pairs have multifractal properties.

Then, we computed the generalized Hurst exponent $h_{xy}(q)$ for the two time series pairs. Figure 9 shows that the generalized Hurst exponents for the time series pairs are not fixed values. $h_{xy}(q)$ decreased with the increase of q, which shows that both the time series pairs have multifractal characteristics. We observed that when $q = 2$, the parameters $h_{xy}(2)$ for both Temperature/FBD and Humidity/FBD are 1.1592 and 1.0963 (see Table 2), respectively; both are greater than 0.5, which means that small and large fluctuations have significant positive persistence. Moreover, the $h_{xy}(2)$ value of Temperature/FBD is larger that of Humidity/FBD, which indicates that the cross-correlation between temperature and bacterial FBD is more persistent than that between humidity and bacterial FBD.

For the two time series, when q below 0, the value of $h_{xy}(q)$ decreased rapidly with increasing q; this shows that wavelet fluctuations have significant positive persistence. On the other hand, when $q > 0$, with increasing q, $h_{xy}(q)$ stayed low, which means the minimum sustainability of large fluctuations.

$$\Delta H_{xy}(q) = h_{xy}(q_{\min}) - h_{xy}(q_{\max}). \tag{16}$$

According to Eq. (16), we calculated the degree of multifractality $\Delta H_{xy}(q)$ for each time series pair and list the values related to the multifractality in Table 2. We noticed that with increasing

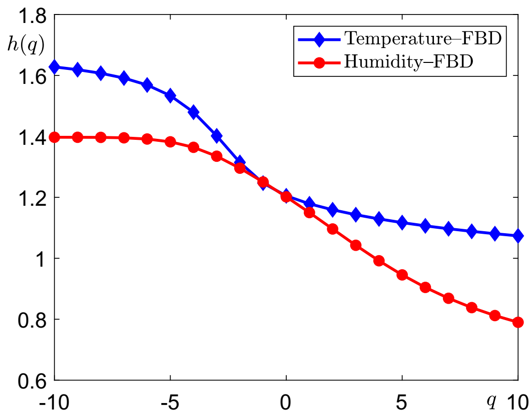


Fig. 9 Hurst exponent of Temperature/FBD and Humidity/FBD.

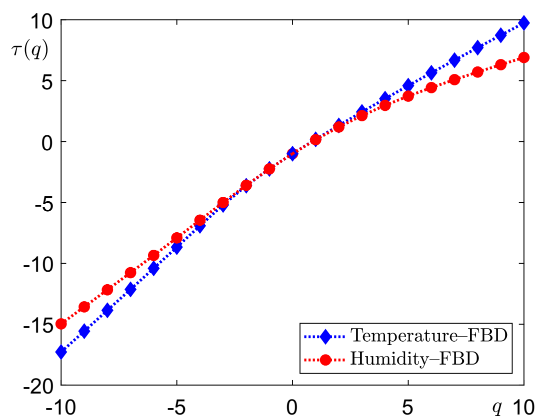


Fig. 10 Scaling exponent curve of Temperature/FBD and Humidity/FBD.

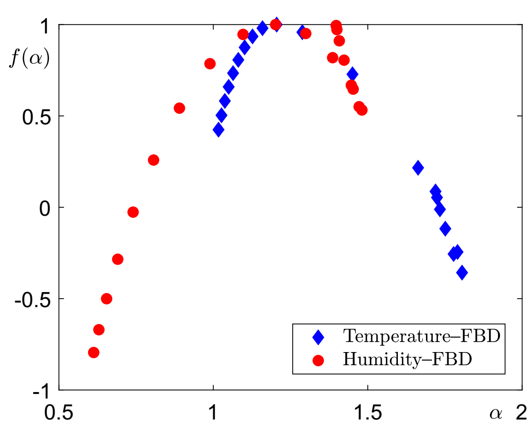


Fig. 11 Multifractal spectrum of Temperature/FBD and Humidity/FBD. For interpretation of the references to color in the figure, the reader is referred to the web version of the paper.

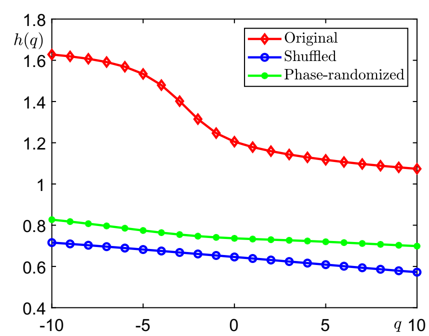
Table 2 Multifractality of Two Time Series Pairs Temperature/FBD and Humidity/FBD.

	$h(2)$	$\Delta H(q)$	$\Delta\alpha$
Temperature/FBD	1.1592	0.5545	0.7885
Humidity/FBD	1.0963	0.6072	0.8685

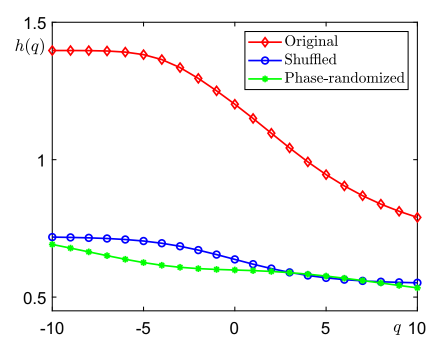
q, the range of $h_{xy}(q)$ fluctuations of Humidity/FBD is larger. This indicates that its multifractal characteristics are stronger and the cross-correlation of the time series between humidity and FBD is greater than that between temperature and FBD.

The scaling exponent $\tau_{xy}(q)$ plotted in Fig. 10 becomes nonlinearly increasing with increasing q. This shows further support for the multifractality of the two time series pairs, and is consistent with the results calculated from generalized Hurst exponents.

Finally, we examine the two time series pairs using the multifractal strength and spectrum; the correlation curves between α_{xy} and $f_{xy}(\alpha)$ are depicted in Fig. 11. The multifractal spectra are not shown as points, which imply the existence

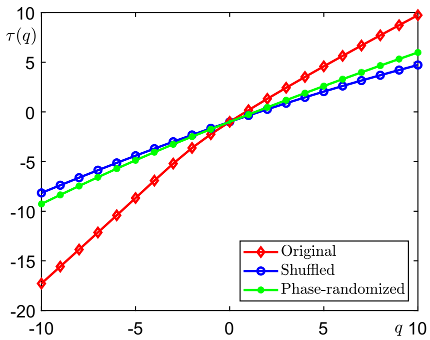


(a) Temperature/FBD

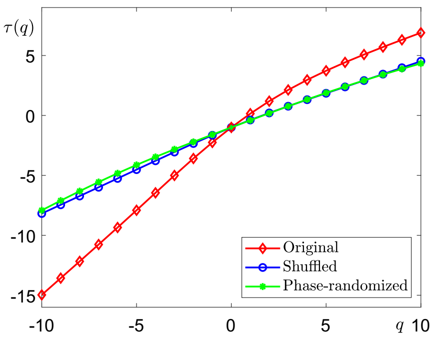


(b) Humidity/FBD

Fig. 12 Hurst exponent of original, shuffled, and phase-randomized time series of (a) Temperature/FBD and (b) Humidity/FBD.

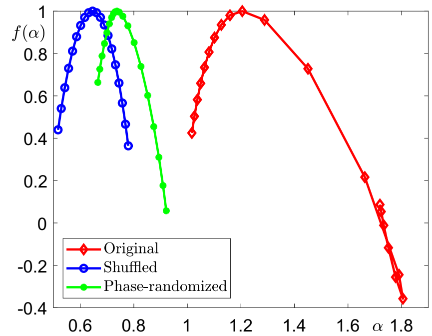


(a) Temperature/FBD

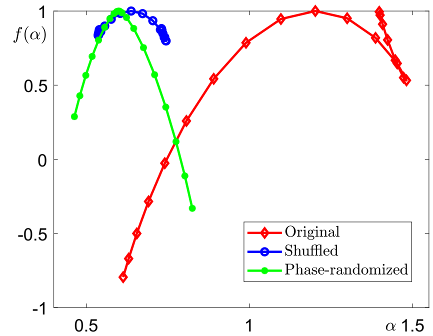


(b) Humidity/FBD

Fig. 13 Scaling exponent curve of original, shuffled, and phase-randomized time series of (a) Temperature/FBD and (b) Humidity/FBD.



(a) Temperature/FBD



(b) Humidity/FBD

Fig. 14 Multifractal spectrum of original, shuffled, and phase-randomized time series of (a) Temperature/FBD and (b) Humidity/FBD.

of multifractality in both time series pairs. We then calculated the widths of the multifractal spectra $\Delta\alpha_{xy}$, and the results are presented in Table 2. From Table 2, the fluctuation range of Temperature/FBD is lower than that of Humidity/FBD, which implies that the multifractality of Humidity/FBD is stronger than that of Temperature/FBD, and FBD is more sensitive to humidity.

4.6. The Sources of Multifractal Features

A previous study[39] documented that the causes of multifractality are long-range correlations and fat-tail distributions. In this section, we discuss the main source of multifractality for each time series pair. To measure the contribution of long-range correlations and fat-tail distributions quantitatively, we constructed shuffled and phase-randomized time series of the original time series, respectively.

Then, we calculated the Hurst exponent $h_{xy}(q)$, scaling exponent $\tau_{xy}(q)$, and $\Delta\alpha_{xy}$ of the original, shuffled, and phase-randomized time series for the two time series pairs. As shown in Figs. 12–14, all the time series are strongly multifractal. $h_{xy}(2)$ (see Table 3) for all shuffled and phase-randomized time series pairs are greater than 0.5, indicating that the positive persistent property exists in all the time series pairs. Moreover, the $h_{xy}(2)$ of shuffled and phase-randomized time series pairs are much lower than the original series pair, which means that the time series pairs become weaker persistent after shuffling and phase-randomization of the original time series pair.

To examine the main cause of multifractality, as shown in Table 3, we show that the widths of the multifractal spectrum of original, shuffled, and phase-randomized series of Temperature/FBD are 0.7885, 0.2625, and 0.2558, respectively. The results indicate that both long-range correlations and fat-tail distribution contribute to multifractality. For the Humidity/FBD series pair, the multifractal spectrum widths of original, shuffled, and phase-randomized series are 0.8685, 0.2082, and 0.3614, respectively. We find that a large part of multifractality was removed by shuffling and phase

Table 3 Multifractality of Original, shuffled, and Phase-Randomized Series for Temperature/FBD and Humidity/FBD.

		$h(2)$	$\Delta\alpha$
Temperature/FBD	Original	1.1592	0.7885
	Shuffled	0.6312	0.2625
	Phase-randomized	0.7299	0.2558
Humidity/FBD	Original	1.0963	0.8685
	Shuffled	0.6037	0.2082
	Phase-randomized	0.5933	0.3614

randomization of the original series pair. Long-range correlation is the major source of the multifractal properties for Humidity/FBD series pair.

5. CONCLUSIONS

In this paper, we first used MF-DFA to investigate the multifractality of two separate time series of temperature and humidity. We found that the power-law behavior and long-range correlations existed in each time series, i.e. both time series have strong multifractality. Then, we employed MF-DCCA to investigate the cross-correlations between bacterial FBD and meteorological factors. We found power-law cross-correlations between bacterial FBD and meteorological factors, and the multifractal properties were significant. Moreover, by calculating the $h_{xy}(2)$, we noted that the cross-correlations between temperature and bacterial FBD are more positive persistent than that between humidity and bacterial FBD. Comparison of the strengths of multifractal spectra showed that the degree of multifractality of the Humidity/FBD time series pair is greater than that of the Temperature/FBD; this indicates that the monthly number of outpatient FBD cases is more sensitive to humidity. To document the major source of multifractality, we shuffled the original series. The results show that both the long-range correlations and fat-tailed distribution contribute to the multifractality of the cross-correlations between the temperature and bacterial FBD time series. For the Humidity/FBD series pair, the major source is the long-range correlations. We believe that our findings can accelerate development of disease prediction models in response to climate change.

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