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Research Article

Scale Analysis and Correlation Study of Wildfire and the Meteorological Factors That Influence It

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Wildfire is a large-scale complex system. Insight into the mechanism that drives wildfires can be revealed by the distribution of the wildfire over a large time scale, which is one of the important topics in wildfire research. In this study, the scaling properties of four meteorological factors (relative humidity, daily precipitation, daily average temperature, and maximum wind speed) that can affect wildfires (number of wildfires per day) were investigated by using the detrended fluctuation analysis method. The results showed that the time series for these meteorological factors and wildfires have similar power exponents and turning points for the power exponents curve. The five types of time series have a lasting and steady long-range power law correlation over a certain time scale range, where the corresponding exponents were 0.6484, 0.5724, 0.8647, 0.7344, and 0.6734, respectively. They also have a reversible long-range power law correlation beyond a certain time scale, where the corresponding exponents are 0.3862, 0.2218, 0.1372, 0.2621, and 0.2678. The multifractal detrended fluctuation analysis results showed that the wildfire time series were multifractal. The results of the research based on the detrended cross-correlation analysis and the multifractal detrended cross-correlation analysis showed that relative humidity and daily precipitation have a considerable impact on the wildfire time series, while the impacts of daily average temperature and the maximum wind speed are relatively small. This study showed that identifying the factors causing the inherent volatility in the wildfire time series can improve understanding of the dynamic mechanism controlling wildfires and the meteorological parameters. These results can also be used to quantify the correlation between wildfire and the meteorological factors investigated in this study.

1. Introduction

Forest fires seriously threaten the stability and balance of the forest ecosystem and the health of local people. They are one of the most serious natural disasters because they restrict the sustainable development of modern forestry. It is very important to study the distribution law for forest fire. However, the forest fire system includes several subsystems, such as the climate subsystem of the forest region, the geographical subsystem, and human production and lifestyle customs. Therefore, the forest fire system is a typically complex system in nature. Many time series in nature have fractal scale behaviors, such as the time series for statistical physics [1–3], meteorology [4, 5], geography [6], and information science systems [7]. The fractal or multifractal mechanism of the system is characterized by a scale exponent or multiple scale exponents. The fractal or multifractal features of the system can be also characterized by a scale exponent or multiple scale exponents. The significance of these features can be used to model the time series and predict the future behavior of extreme wildfire events.

The uncertainty of forest fires caused by human activity and lightning strikes meant that wildfire researchers thought that fire was randomly distributed and that it is impossible to forecast wildfire risk reliably. Bak et al. (1990) introduced a forest fire model that they claimed to show self-organized criticality [8]. Then this model was revised by Drossel et al. [9] to overcome the disadvantage that a fire propagates on regular fronts that proceed with a finite velocity and burn down a finite number of trees [10]. This characteristic demonstrated that wildfires automatically reach a steady state and that this is characterized by the power law relationship between the 'frequency-size' distributions for forest fires [9]. Since then, researchers have found a theoretical basis for predicting forest

fires. Malamud et al. and Song et al. used some real forest fire data from the United States and Australia to show that, if given enough data over several years, they could forecast how large the average 10 or 50 year fire will be [11, 12]. However, these studies were only based on the forest fires recorded by State Forestry Administration of the People's Republic of China and urban fires recorded by the fire department of the Ministry of Public Security of the People's Republic of China. It is possible to use the area of a forest fire as a scale [13] when studying forest fires and the economic losses from fire as an indicator [14] of urban fire damage because both satisfy the power law feature. There are no fire records about small fires that may extinguish spontaneously or be put out by residents. Therefore, it may be very difficult to evaluate fire scale by using the area of a forest fire (the number of trees burned by fire) and the economic losses caused by a city fire. Previous research failed to consider the distribution features of these small wildfires due to a lack of information on the number of fire occurrences, fire hotspot regions, and the area of vegetation burnt.

It has been shown that external meteorological factors are the root causes of the power law time distribution for wildfire [15, 16]. However, the time interval for these studies is the minute. The total length of the forest fire time series is 200 days. When the length of the times series is greater than 200 days, the scale behaviors of forest fire times series are unclear. Song pointed out that meteorological factors [17], such as relative humidity, precipitation, temperature, and wind speed, can influence the forest fire distribution. However, there have been no studies on the correlation between these meteorological factors and forest fires. Furthermore, meteorological factors, especially daily precipitation and relative humidity, are coupled to each other. There have also been no studies on the impacts of meteorological factors on forest fires.

The fractals for actual complex systems in nature are different from pure mathematical theory. The fractal features mostly only exist for a certain time scale range called the scale-free interval. It is not known whether the fractal for wildfire is within the unmarked range. The physical significance of the scale size is not clear. The characteristics of the existing macroscopic wildfire data suggest that the nature of micro-wildfires can be inferred. This information can be used to explore new ideas and approaches to wildfire prediction and control. Furthermore, the occurrence of wildfire is due to the coupling of various complex factors, which means that finding the correlation between coupling factors and fire is a key area of research.

In this study, the long-range correlations between the wildfire time series (number of wildfires per day) and meteorological factors (relative humidity, daily precipitation, daily average temperature, and maximum wind speed) were studied using statistical analysis (detrended fluctuation analysis [DFA], detrended cross-correlation analysis [DCCA], multifractal detrended fluctuation analysis [MF-DFA], and multifractal detrended cross-correlation analysis [MF-DCCA]). The scale characteristics of wildfire and the main external driving factor time series (meteorological factors) were compared; the scale invariance features of the wildfire time series were determined; and the relationships and differences between wildfire time series and meteorological factors were investigated.

2. Area and Data Resources

Hunan Province is located in the southern part of China. It has a total area of 211,800 km^2 and a population of 65 million. Hunan is in the continental subtropical monsoon humid climate zone. It has a short winter and a long frost-free-period. The sunshine lasts for long periods of time during the day and the four seasons are clearly distinguished. The annual average temperature is 16°C–18°C (60.8°F–64.4°F), and the annual average rainfall is between 1200 and 1700 mm. During the Qingming and Spring Festivals, tomb sweeping is one of the most important and popular ways to show respect to ancestors by burning paper, incense, or firecrackers at the columbaria, graves, or burial grounds. However, these activities often cause forest fires. Furthermore, setting fire to a certain area of forest to burn weeds to make fertilizer and to open up new farmland has been passed down for generations. Ashes from such human-caused fires often lead to local fires.

The raw wildfire data from the satellite monitoring system were processed by removing industrial and urban fires from the analysis. This left 376,695 Chinese sets of data that covered January, 2007 to December, 2012. There were 23,074 wildfires in Hunan Province. The source of the fire information was data from the Moderate-Resolution Imaging MODIS sensor onboard the National Aeronautics and Space Administration's (NASA) Earth Observing System satellites, Terra and Aqua, launched December, 1999 and May, 2002, respectively. This data set was provided by the University of Maryland and the NASA Fire Information for Resource Management System operated by the NASA/Goddard Space Flight Center/Earth Science Data Information System with funding provided by NASA.

The meteorological data came from the Data Application Service Room of the National Meteorological Information Center, China. This study used daily data sets for Chinese surface climate data, which include relative humidity (1%), cumulative precipitation at 20–20 (0.1 mm), average temperature (0.1°C), and maximum wind speed (0.1 m/s) data from 14 ground meteorological stations in Hunan Province, such as Shaoyang, Shuangfeng, and Zhuzhou. There were 107,004 Chinese sets of data that covered the period 2007 to 2012. In total, there were 483 invalid values for maximum wind speed, four invalid values for average temperature, four invalid values for relative humidity, and no invalid values for cumulative precipitation at 20–20 in the data sets.

3. Scale Behavior of Wildfires Derived from the Satellite Remote Sensing Data

3.1. Seasonal Distribution of Wildfires. Figure 1 shows that the distribution of the wildfire time series in Hunan Province has a very obvious seasonal pattern, and the peak values for the most wildfires per day appear in February and April every year. The meteorological data for Hunan Province over this period suggest that this may be because

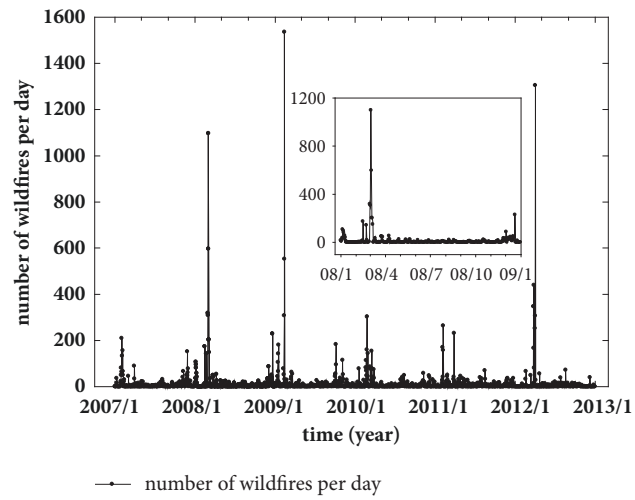

Figure 1: Seasonal distributions of wildfires in Hunan Province from 2007 to 2012.

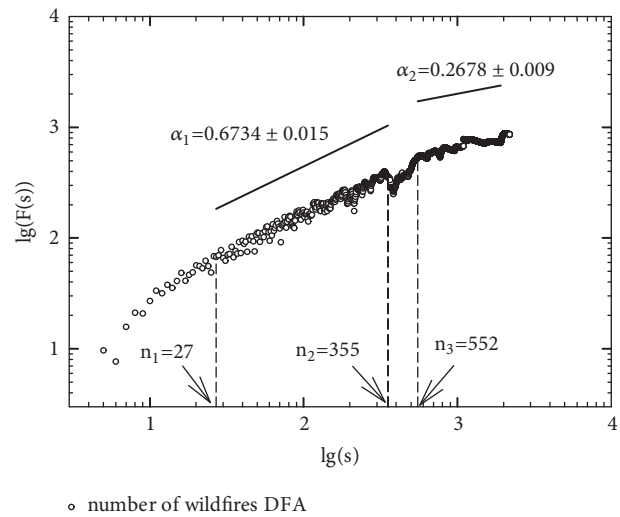

Figure 2: Scaling behaviors of wildfire time series.

(1) Setting off firecrackers and ancestor worship during the Spring Festival, Swidden cultivation during the busy spring plowing season, and the Ching Ming festival ceremonies increase the potential wildfire sources.

(2) Major snowstorm events leave vegetation vulnerable to die-back and breaking in the winter, which leads to a decrease in vegetation water content.

(3) Wildfires are fueled by dry conditions and high or variable winds. Higher temperatures, longer hours of hot sunshine, and low humidity occur at the end of the winter or in early spring and these conditions may increase the potential for wildfires.

3.2. Multiscale Exponent Characteristics of Wildfire Time Series. Malamud et al. (1998), Ricotta et al. (1999), and Doyle et al. (2000) showed that forest fire time series cannot be simply regarded as random processes with a Poisson distribution. Wildfire occurrences are affected by multiple coupled, complex systems, such as human activities, lightning, and precipitation. Therefore, the wildfire time series is nonstationary and has obvious nonlinear features. The external manifestation is that time series not only has nonstationary features, but also chaotic and fractal characteristics, which will lead to specific time scales having self-similarities. These different self-similarity features reflect the dynamic characteristics of the time series at different time scales. The detrended fluctuation analysis (DFA) [18] is more effective than the traditional sequential analysis method at determining these features.

In Figure 2, s means the time scale and F(s) means the fluctuation magnitude. Figure 2 shows that there are significant long-term correlations between the wildfire time series when the time scale is > 27 days and < 355 days. This means that the number of wildfires per day is not a random process, but a partially random process. The occurrence of wildfires in the past will affect the current and future number of wildfires per day. The future trend for a wildfire time series is positively correlated with its historical trend, and the larger the scale exponent is, the stronger the positive correlation is. The turning point for a time scale is about 355 days. A year is 365 days (or 366 days). Therefore, the turning point of the scale curve may correspond to the nature taking 1 year or four seasons to cycle. Satellite scanning cycle limitations mean that it is difficult to confirm the dynamic small time scale characteristics of wildfires, such as at the minute-level. When the time scale is > 552 days, which exceeds the maximum characteristic time scale of a wildfire, the slope of the scale curve tends to zero, which means that there are no longer any correlations at that time scale.

3.3. Multifractal Characteristics of Wildfire Time Series. A new DFA method was used to study the multifractal characteristics of nonstationary time series, which was named the multifractal detrended fluctuation analysis (MF-DFA) method [19]. The basic algorithm of the MF-DFA method is similar to the DFA algorithm. However, the MF-DFA method introduces parameter q to get the q-order fluctuation function $F_q(s)$ at the fourth step, which means that the wave function can be found.

$$F_q(s) = \left\{ \frac{1}{2N_s} \sum_{\nu=1}^{2N_s} \left[F^2(\nu, s) \right]^{q/2} \right\}^{1/q} \tag{1}$$

where N_s represents the number of sections that the wildfire or meteorological time series are segmented into, and $N_s = [n/s]$.

The log-log plots of parameter s versus function $F_q(s)$ allow the scale behavior of the wave function to be studied. If the sequence has long correlation properties, then $F_q(s)$ has a power law relationship with s, $F_q(s) \sim s^h(q)$. The slope h is called the generalized Hurst exponent. When $q < 0$, the size of $F_q(s)$ depends on the size of the small fluctuation deviation $F^2(\nu, s)$. When $q > 0$, the size of $F_q(s)$ depends on the magnitude of large fluctuation deviation $F^2(\nu, s)$.

When $h(q)$ approaches 0, the time series has a strongly inverse correlation. At this point, the DFA method cannot

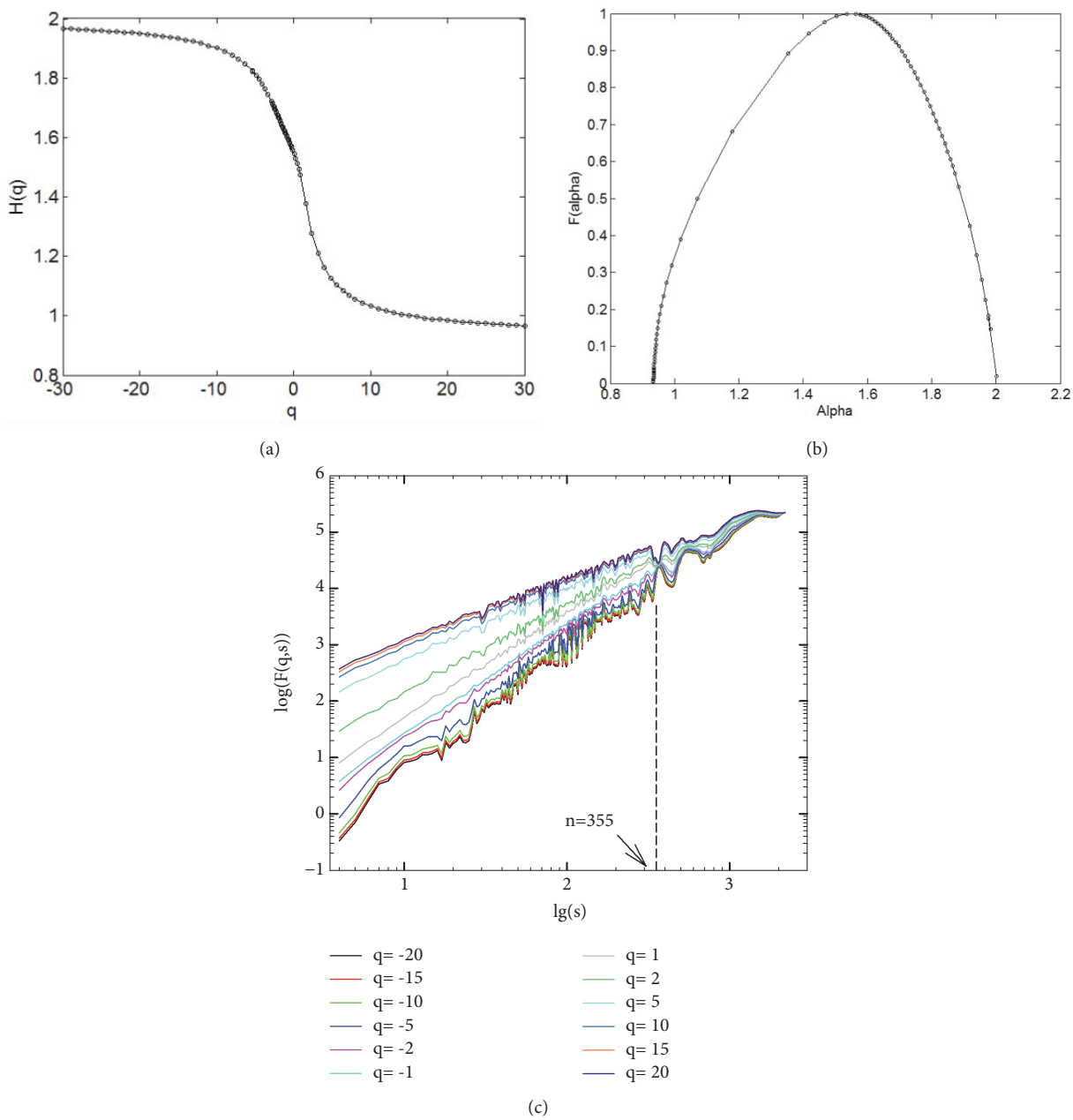

Figure 3: Scale-free features of wildfire time series based on the MF-DFA results. (a) Generalized Hurst index for wildfire time series; (b) the multispectrum parameters F (alpha) and singular exponent (Alpha) changes in the wildfire time series; and (c) wave functions $\widetilde{f}_{\mathrm{q}}(s)$ and s changes in the wildfire time series.

determine the nature of the time series accurately. However, this study used a modified MF-DFA procedure [20]. The improvement over the DFA method is that the general MF-DFA method can be used to calculate the cumulative dispersion twice in the first step:

$$\widetilde{Y}(i) \equiv \sum_{k=1}^{N} [Y(k) - \langle Y \rangle] \tag{2}$$

Then the generalized wave function $\widetilde{F}_{\mathrm{q}}(s)$ can be obtained.

$$\widetilde{F_{\mathrm{q}}}(s) \sim s^{\widetilde{h}(q)} \tag{3}$$

The wildfire time series were analyzed using the modified MF-DFA method, and the generalized Hurst exponent curve and multifractal spectrum curve were obtained, as shown in Figures 3(a) and 3(b), respectively. Figure 3 shows that in the generalized Hurst exponent of the time series for wildfire, $\widetilde{h}_{\mathrm{q}}(q)$ is the decreasing function of the q order, and function $f(\alpha)$ has a single bell shaped peak with good symmetry, which indicates that the wildfire time series has strong autocorrelation and fractal and cross-weight fractal features. A wildfire time series has different scale characteristics. When $q > 10$, the scale index represents the scale behavior of large fluctuations. Furthermore, the generalized Hurst exponent is

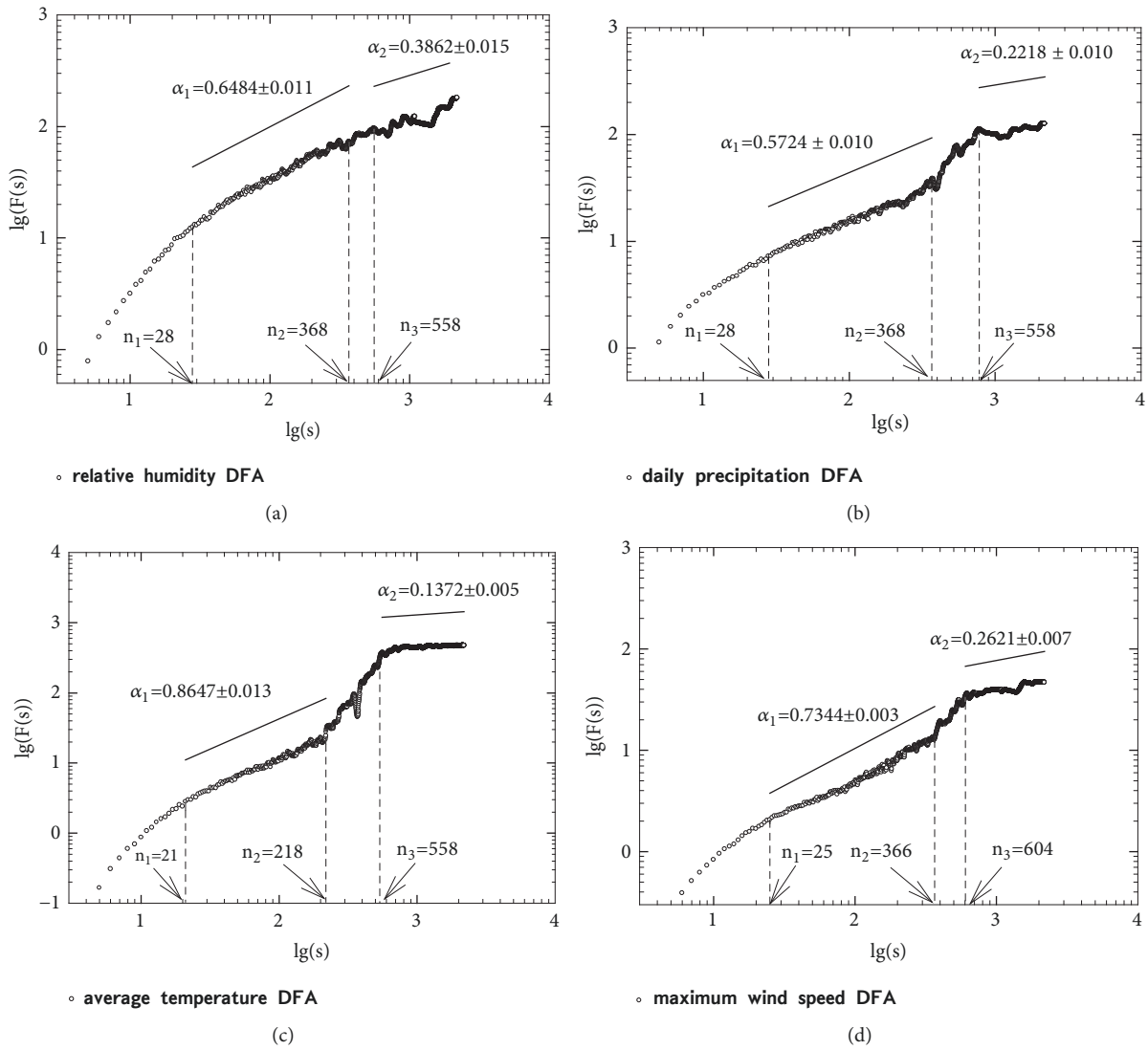

Figure 4: Scale-free features of the meteorological factor time series based on the DFA. (a) Scale-free features of the relative humidity time series from 2007 to 2012; (b) scale-free features of the daily precipitation time series from 2007 to 2012; (c) scale-free features of the daily average temperature time series from 2007 to 2012; and (d) scale-free features of the maximum wind speed time series from 2007 to 2012.

approximately equal to 0.92 for a wildfire time series. This indicates that there is a long-term power law correlation between wildfires.

When q takes different values, the wave functions curve has a distinctly linear interval. Figure 3(c) shows that, in the scale-free range, when the time scale is short, a negative order q corresponds to a large wave function for numerical change, while a positive order q corresponds to a small wave function for numerical change. This result indicates that a small fluctuation deviation plays a decisive role in wildfire data. When the time scale is long, a negative order q corresponds to a small wave function for numerical change, while a positive order q corresponds to a large wave function for numerical change, which indicates that a large fluctuation deviation has a decisive effect on the wildfire data. This may be because the meteorological factors that drive wildfires do not differ to any great extent over a short period of time, which means that the fluctuation deviation is small. The variability of the meteorological factors increased greatly as the time scale rose.

4. Analysis of the Formation Mechanism for Wildfire Scale Behavior

4.1. Scale Behavior Comparisons between Wildfire and Meteorological Factors. The time series for meteorological data, such as relative humidity, precipitation, daily average temperature, and maximum wind speed, were analyzed using the DFA method so that the relationships between the wildfire time series and meteorological factors could be determined. The obtained scaling curves are shown in Figure 4. The time series scale curves of the above-mentioned four meteorological factors all have turning characteristics. A comparison between Figures 2 and 4 and Table 1 shows that the wildfire time series and the meteorological factor time series have

Table 1: DFA characteristic parameters for the wildfire and meteorological factor time series.

Type of time series	α_1	α_2	n_1	n_2	n_3
number of wildfires per day	0.6734	0.2678	27	355	552
relative humidity(%)	0.6484	0.3862	28	368	558
daily precipitation(mm)	0.5724	0.2218	28	368	778
daily average temperature(°C)	0.8647	0.1372	28	218	558
maximum wind speed(m/s)	0.7344	0.2621	25	366	604

many similarities. The turning point and scale index of the corresponding scale have clear characteristics.

① The time scale characteristics of the number of wildfires per day time series have many similarities with those of the four researched meteorological factors. They all have three inflection points, which are n1, n2, and n3 and divide the entire time series into two different intervals with scaling exponents equal to $\alpha 1$ and $\alpha 2$. For all five time series (wildfire and four meteorological factors), when the time scale is > n1 and < n2, $\alpha 1$ is > 0.5 and < 1, which indicates a stable positive correlation at the right time scale. The position of the turning point n1 is very similar at around 26 days. When the time scale is > n3, $\alpha 2$ is < 0.5. This shows that there is a negative correlation for the time scale. In addition, the turning point for the daily average temperature time series is 218, but the turning points (n2) for the four meteorological time series are 355–368 days. This suggests that the turning point of the scale curve corresponds to the natural four-season 365-day cycle.

② When the time scale is relatively small, and its scale exponent is large, the mechanism cannot be clearly explained due to meteorological satellite monitoring time scale limitations.

③ In particular, the variation characteristics of the scale indexes for precipitation, temperature, and maximum wind speed are more similar than the relative humidity and wildfire variation characteristics. When the time scale is > n1 and < n2, scale exponent $\alpha 1$ is > 0.5 and < 1. If the time scale is increased, the scaling exponent oscillates considerably when the time scale is > n2 and < n3. The changes in the scale characteristics for the relative humidity and wildfire time series are much more moderate, and the turning point is not particularly obvious.

④ In these five time series, the scale exponent for temperature is the largest and the scale exponent for daily precipitation is the smallest.

The results show that the time series for wildfire and meteorological factors are connected and that there is no single scalar behavior for the five time series. Therefore, a single scale index cannot be used to describe the dynamic properties of the five time series.

4.2. Detrended Cross-Correlation Analysis

4.2.1. DCCA Method. It is difficult to determine the effects of meteorological factors on wildfires using traditional methods. This study adopted the DCCA method to study the cross-correlation between time series for wildfires and the meteorological factors that influence them [21].

The DCCA can be used to calculate the cross-correlation between two nonstationary time series, and its basic steps are similar to the DFA method. Supposing there are two time series, $\{x_k,\ k = 1, 2, 3 \ldots, N\}$ and $\{x'_k, k = 1, 2, 3 \ldots, N\}$, where N is the length of the time series, then the accumulated deviation of the two time series, $Y(i)$, $Y'(i)$, can be calculated using

$$Y(i) = \sum_{t=1}^{i} (x(t) - \overline{x}) \tag{4}$$

$$Y'(i) = \sum_{t=1}^{i} \left(x(t)' - \overline{x'}\right) \tag{5}$$

where $i = 1, 2, 3\ldots$, n.

Secondly, the $Y(i)$ and $Y'(i)$ data is segmented into equal m sections with s as their length and where m = [n/s]. As the length of the sequence is not always an integral multiple of s, a small amount of the data at the end is not used. To make full use of the data resource, the same sequence is subjected to the same actions again, only in reverse order, which means that the sequence is equally segmented into 2 m sections.

Thirdly, the least square method can be used to fit the s data in each division, which gives the local trends. After removing the local trends, the difference between the original time series and the fitting values, $Yi(s)$ and $Y's(i)$, can be obtained by using

$$Y_s(i) = Y_i - P_\nu(i) \tag{6}$$

$$Y'_s(i) = Y'_i - P'_\nu(i) \tag{7}$$

Fourthly, the variances for the s data, after they had been detrended in each division, are calculated using

$$f^2_{DCCA}(v_1, s) = \frac{1}{s}\sum_{i=1}^{s} \left(Y_k - P_{\nu 1}(i)\right)\left(Y'_k - P'_{\nu 1}(i)\right) \tag{8}$$

$$f^2_{DCCA}(v_2, s) = \frac{1}{s}\sum_{i=1}^{s} \left(Y_k - P_{\nu 2}(i)\right)\left(Y'_k - P'_{\nu 2}(i)\right) \tag{9}$$

where $v_1 = 1, 2, 3\ldots, m$; $v_2 = m + 1, m + 2, m + 3\ldots, 2m$; $P_{v1}(i)$ and $P'_{v1}(i)$ are the fitting polynomials of the corresponding intervals for $Y_s(i)$ and $Y'_s(i)$, respectively.

Fifthly, the trends within the division are eliminated by subtracting them from the accumulated time series in each

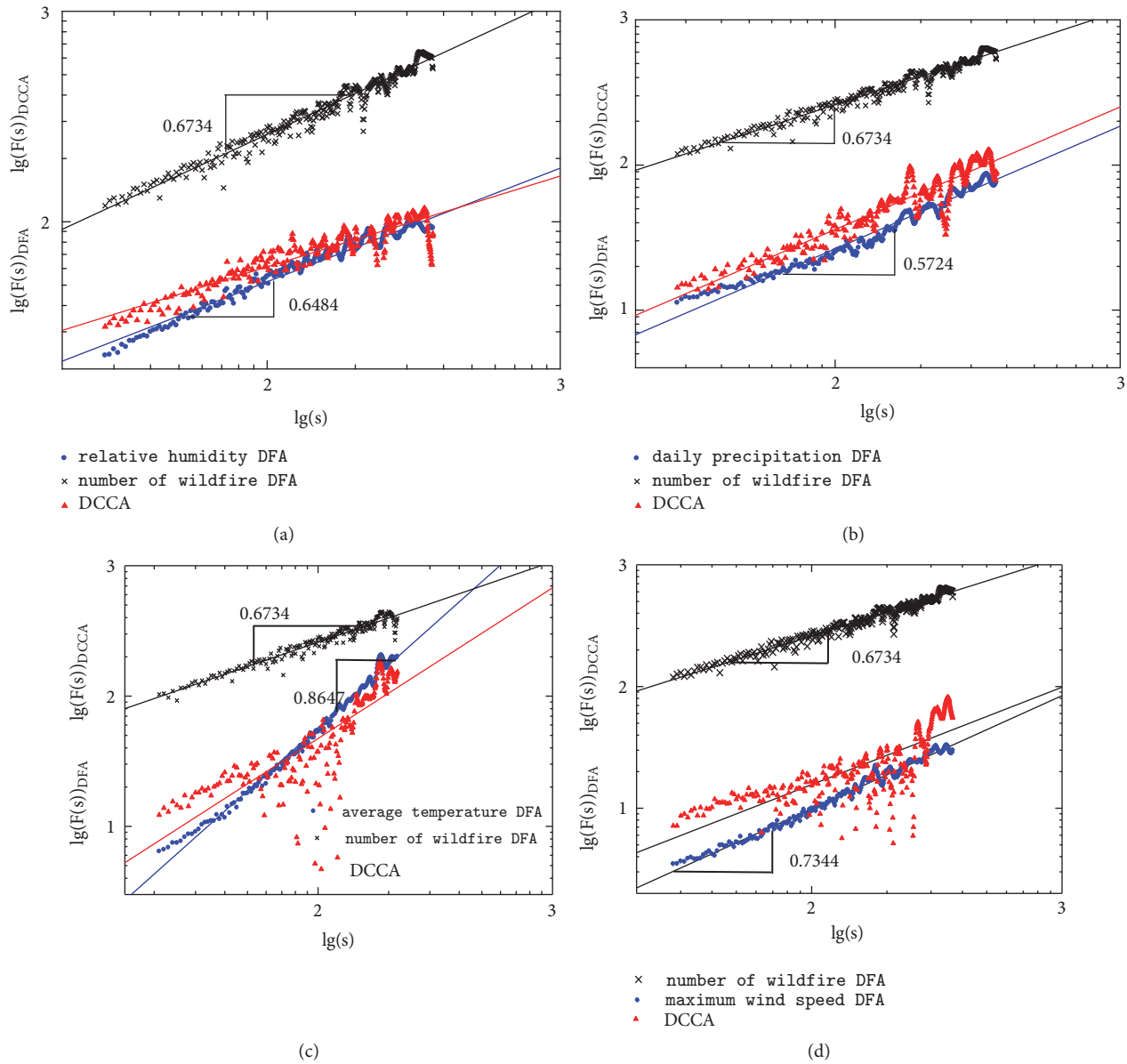

FIGURE 5: Cross-correlation analysis of wildfire and meteorological factor time series based on DCCA. (a) The cross-correlations between the relative humidity and wildfire time series; (b) the cross-correlation between the daily precipitation and wildfire time series; (c) the cross-correlation between the daily average temperature and wildfire time series; and (d) the cross-correlation between the maximum wind speed and wildfire time series.

division. This process was applied to every division and the detrended cross-correlation magnitude $F_{DCCA}(s)$ is defined as

$$F_{DCCA}(s) = \sqrt{\frac{1}{2m}\sum_{\nu=1}^{2m}\left[f^2(\nu, s)\right]} \tag{10}$$

Sixthly, $F_{DCCA}(s)$ to s relationship in double logarithmic coordinates was obtained. Then a curve was fitted to $F_{DCCA}(s)$ and s using the least square method, so that the scaling exponent λ could be obtained:

$$F_{DCCA}(s) \sim s^{\lambda} \tag{11}$$

Scaling exponent λ denotes the degree of correlation between the two types of time series: x_k and x'_k. Section 4.1 suggests that when the data is recorded using the lowest time unit (1 day), the time series for the number of wildfires per day and the meteorological factors meet the long-term correlation for the 25 d to 365 day time range. This means that time scales that are smaller than the scale-free zone are not included in the calculation, which is consistent with the literature for method research (Shao et al. 2012). Therefore, the time scale used when studying the correlation along the time series for meteorological factors and wildfire was 25 to 365 days (Figure 5).

The values of scaling exponent λ were 0.53 and 0.84, respectively (Figures 5(a) and 5(b)). In Figures 5(c) and 5(d), when the time scale is greater than 55 days, the cross-correlation no longer satisfies the power law property. It

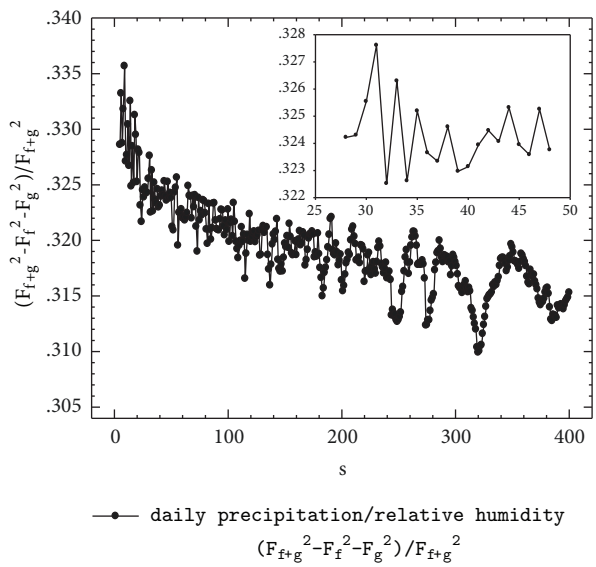

Figure 6: Significance levels of the correlation coefficients between daily precipitation and relative humidity.

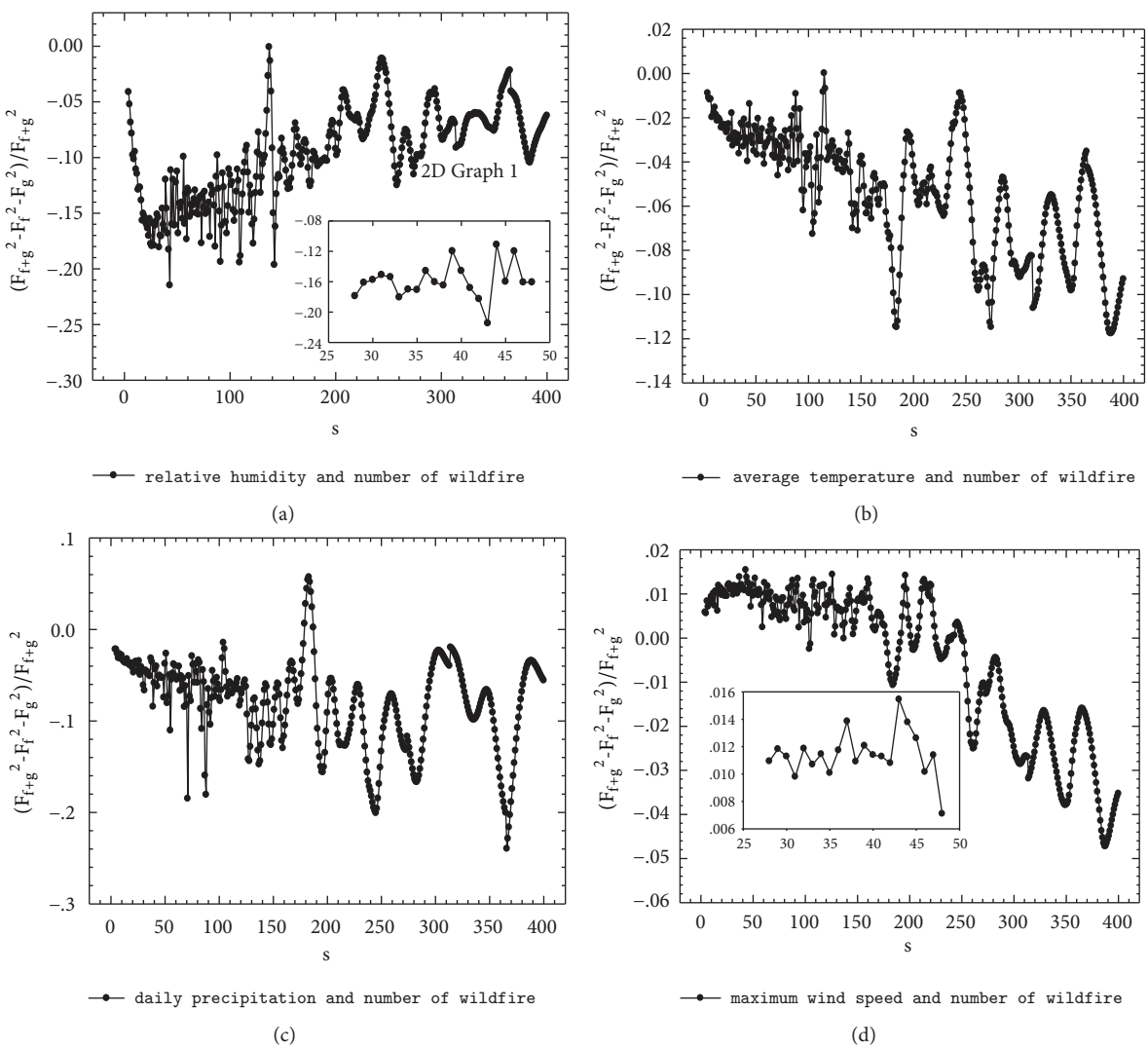

Figure 7: Significance levels of the correlation coefficients between the wildfire and meteorological data time series, (a) significance levels of the correlation coefficients between wildfire and relative humidity; (b) significance levels of the correlation coefficients between wildfire and daily average temperature; (c) significance levels of the correlation coefficients between wildfire and daily precipitation; and (d) significance levels of the correlation coefficients between wildfire and maximum wind speed.

can be seen that the correlations between the time series for wildfire and relative humidity or daily precipitation are greater than those between the time series for wildfire and daily average temperature or maximum wind speed. According to Lin et al. [22], if there are two time series, $f(i)$, $g(i)$, and there is no cross-correlation between the two time series, the relationship $F^2{}_{f+g} \approx F^2{}_f + F^2{}_g$ should hold true. To expatiate the cross-correlation along the time series for meteorological factors and wildfire more clearly, this study defines the intercorrelation significance level between time series as $|(F^2{}_{f+g} - F^2{}_f - F^2{}_g)/F^2{}_{f+g}|$.

When the results in Figures 6 and 7 are combined, the significance levels of the correlation coefficient between daily precipitation and relative humidity are more than 30%. Therefore, the correlation between relative humidity and daily precipitation is very strong. The significance levels of the correlation coefficients between wildfire and relative humidity and between wildfire and daily precipitation are ~10%, which shows that they are also strongly correlated. However, the correlation coefficients between the wildfire time series and daily average temperature and maximum wind speed were significantly lower, which meant that they were weakly correlated.

4.2.2. MF-DCCA. In this study, the cross-correlations in the time series for wildfire, relative humidity, daily precipitation, daily average temperature, and maximum wind speed were analyzed using the MF-DCCA method [23] and the results are shown in Figure 8. The scaling exponent of the cross-correlation between the time series for relative humidity and wildfire satisfies dh(q) / dq < 0. This is also true for the scaling exponent of the cross-correlation between the time series for daily precipitation and wildfire. The results show that the time series for daily precipitation, relative humidity, and wildfire have a strong multifractal nature.

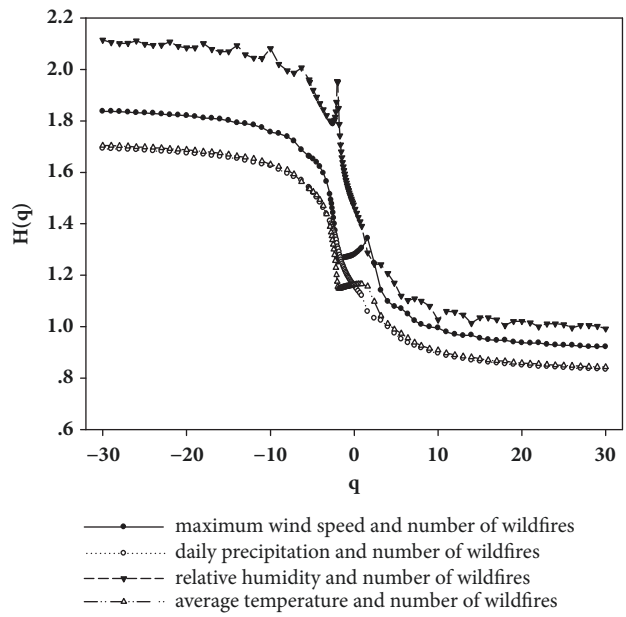

Figure 8: Cross-correlation analysis of the wildfire and meteorological factor time series based on the MF-DCCA.

5. Conclusion

The time series for wildfire has nonstationary characteristics. The DFA and DCCA methods were used to study the fractal features of wildfires.

① The DFA method was used to study the time series for wildfire, relative humidity, daily precipitation, daily average temperature, and maximum wind speed. The results showed that the above five time series have similar scaling behaviors. All the time series had stable positive correlations over smaller time scale ranges, but the relationship was reversed over larger time scales.

② The wildfire time series was analyzed using the MF-DFA method. It had multiple fractals, and the characteristics of the wildfire multifractals were analyzed by combining the meteorological factors.

③ The DCCA and MF-DCCA methods were used to study the cross-correlation between the wildfire, relative humidity, precipitation, daily average temperature, and maximum wind speed time series. The results showed the degree of correlation between wildfire and the meteorological factors.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest related to this work.

Authors' Contributions

Jiazheng Lu contributed paper conception and design. Bo Li carried out data collection. Tejun Zhou performed data analysis. Chuanping Wu wrote the Paper.

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