Long-range Dependence Characteristics of Forest Biological Disasters in China against the Background of Climate Change

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Abstract Forest biological disasters (FBD) seriously impact energy flow and material cycling in forest ecosystems, while the underlying causes of FBD are complex. These disasters involve large areas and cause tremendous losses. As a result, the occurrence of FBDs in China (CFBD) threatens the country's ability to realize its strategic target of increasing both forested area (40 million ha) and forest volume (1.3 billion m^3) from 2005 to 2020. Collectively, China has officially named this effort to increase forest area and volume the "Two Increases" as national goals related to forestry. Based on Hurst index analysis from fractal theory, we analyzed the time series of the occurrence area and related data of FBDs from 1950 to 2007 to quantitatively determine the patterns of the macro occurrence of FBDs in China. Results indicates that, the time series of (CFBD) areas is fractal (self-affinity fractal dimension $D = 1.3548$), the fluctuation of (CFBD) areas is positively correlated (auto-correlation coefficient $C = 0.2170$), and the occurrence of the time series of (CFBD) is long-range dependent (Hurst index $H = 0.6416$), showing considerably strong trend of increases in FBDC area. Three different methods were further carried out on the original time series, and its two surrogate series generated by function surrogate in library *t* series, and function SurrogateData in library in Wavelet software R, so as to analyze the reliability of Hurst indexes. The results showed that the Hurst indices calculated using different estimation methods were greater than 0.5, ranging from 0.64 to 0.97, which indicated that the change of occurrence area data of FBDs was positively autocorrelated. The long-range dependence in forest biological disasters in China is obvious, and the spatial extent of FBDs tended to increase during this study period indicating this trend should be expected to persistent and worsen in the future.

Key words Forest pests and diseases, Hurst index, Long-range correlation, *R/S* analysis

1 Introduction

Most major forest disasters in China can be classified as forest biological disasters[1]. China's FBDs, caused by harmful forest organisms, cover the greatest area and create the heaviest losses of any type of disaster in China; FBDs impact China more heavily than most of the world's countries[2]. A census by Yan and Chai (2006) documented more than 8000 forest pests and diseases, including 292 harmful organisms; these impact 8.7 million ha annually causing the death of more than 400 million trees as a result of forest pests, diseases and other biological disasters; these FBDs result in a reduction of 17 million cubic meters of wood production, which is equivalent to more than 25.13 million ha of forest area or about 6% of China's annual plantation area production. Similar to floods or fires, FBDs are dangerous and destructive to forests, and in particular, such disasters are difficult to manage because they are repetitive with long-term consequences[1]. FBDs in China are expected to become increasingly severe as global warming increases the frequency of weather-related disasters, which are expected to have greater impacts on international and inter-regional trade and economics[1-2]. On one hand, the factors that lead to FBDs in China are complex[1-3], and the forest ecosystems themselves are complex macro-systems. On the other hand, the dynamic evolution of FBDs possesses some macro-regularities, or general characteristics. Linear regression has been the most widely used method of analyzing trends in FBDs for a given time series[4] because of its simplicity and robustness[5]. Linear regression alleviates unevenness in a data set through calculating the regression slope and correlation coefficient; but linear regression fails to indicate possible trends after a particular study period, and the trends after the particular study period is more important for analyzing climate change[4]. As a result, linear regression is unable to reflect non-linear characteristics of natural phenomena throughout a time series[6]; for example, the long-range dependence in some human and natural phenomena is well known and accepted[7]. Fractal theory based rescaled range analysis, or *R/S* analysis, is suitable for revealing the non-linear macro-regularities of a given time series. Fractal theory has been widely employed in forestry and ecology[8-10], and *R/S* analysis has been an important part of fractal theory, which was devised by H. E. Hurst in the 1950s when he studied the statistical properties of the Nile River overflows[11]. Mandelbrot and Wallis[12-13] tested and improved *R/S* analysis based on fractal theory and the existence of self-similarity of time series. Since its discovery, the Hurst index, H, had been widely used to detect and quantitatively describe the existence of long range dependence in a given time series, including such fields as hydrology[14], environmental science[15-17], climate change[18-19], traffic control[20] and economics and finance[21-23].

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Long-range dependence has also been called long-range correlation[22-23] or long-term memory[7, 22]. The application of *R/S* analysis is increasingly popular in the fields of forestry and ecology. Wang *et al.* (2005)[24] calculated Hurst indices of NOAA/NASA PAL Pathfinder AVHRR Land monthly time series data from 1982 to 2001 in a study of the terrestrial regions of China; they found that 99.5 percent of Hurst indices of the Normalized Difference Vegetation Index (NDVI) time series were greater than 0.5, and mostly higher Hurst indices were distributed in western China, reflecting a stronger persistence in NDVI time series in western China. Based on SPOT-VGT (Système Pour l'Observation de la Terre-Vegetation) data, Hou *et al.* (2010)[25] studied the characteristics and trends of vegetation cover change in China's eastern coastal areas during 1998 – 2008 and found that there was obvious self-similarity and long-range dependence of vegetation cover change; the Hurst index of the entire study area was calculated to be 0.84, indicating the increasing vegetation cover is definitely sustainable in the future. Using the SPOT-VGT NDVI time series data and the spatial distribution of Hurst indices in various land-use types, Wang *et al.* (2010)[26] analyzed the temporal and spatial vegetation cover changes from 1999 to 2007 in Xinjiang Province, China; their results showed a continuous increasing trend for vegetation cover in most parts of Xinjiang. Based on NDVI time series data, similar research studies employing *R/S* analysis were carried out by Zhang and Ren (2010)[27] in Shaanxi Province and by Li and Jiang (2011)[28] in Gansu Province, China. Peng *et al.* (2012) analyzed the Hurst index of an annual average NDVI time series for each vegetation type in the Qinghai-Tibet Plateau during 1982 – 2003 to quantify the consistency of dynamic trends in vegetation cover after the study period. They found modeled future vegetation dynamics for the entire plateau were very consistent, and that areas showing inconsistent trends were mainly meadow and steppe distributed in the central or eastern regions of the plateau. Based on data obtained from sample trees, Luo *et al.* (2007)[29] analyzed the growth process of trees based on their diameters and found that the Hurst index increased with age of the trees. Luo *et al.* (2008)[30] believed that a Hurst index existed in the time series data of diameter growth of trees for different tree species and different ages. However, few of these studies have been concerned with the robustness and validation of *R/S* analysis[18]. As for FBDs in China, few researchers have explored the features of FBDs in relation to the existence of long-range dependence in the time series. FBD research studies are helpful in ascertaining the negative impacts of FBDs on forest resources, forest production and forest ecosystem services; they also enhance our understanding of the status of the losses caused by FBDs and improve our ability to manage FBDs. In particular, in the current context of developing a low carbon economy and tackling climate change, a quantitative description of the macro-regularities of FBDs in China is significantly meaningful to the construction of China's "Three Systems" in forestry, which includes improved ecological forestry system, developed forestry industry system and prosperous ecological culture system. The Three Systems are also designed to help China realize the strategic target of "Two Increases" in forestry, *i.e.*, 1) increases in forested area by 40 million ha and 2) forest volume by 1.3 billion m^3 from 2005 to 2020.

2 Materials and methods

2.1 Data The data of this study are a time series of occurrence area data caused by FBDs in China during the period 1950 – 2007, which were originally published officially by the Forest Pests and Diseases Monitoring and Forecasting Center of the State Forestry Administration of the P. R. China, and which were summarized also by Yan (2009)[31].

2.2 Methods A flow chart was used to generalize data processing procedure (Fig. 1). Based on software R[32], this work's related functions were written in R language to simplify data calculation and display of the results. The functions provided by R were used with default parameters when the option was available.

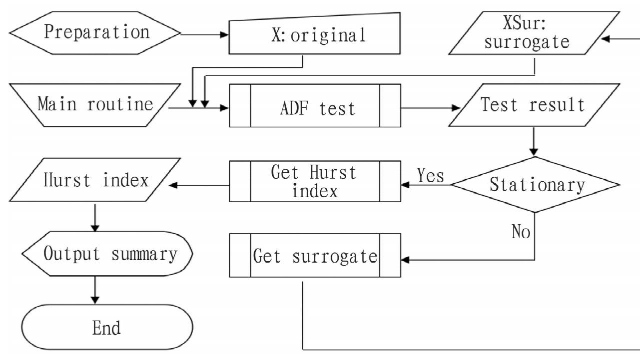
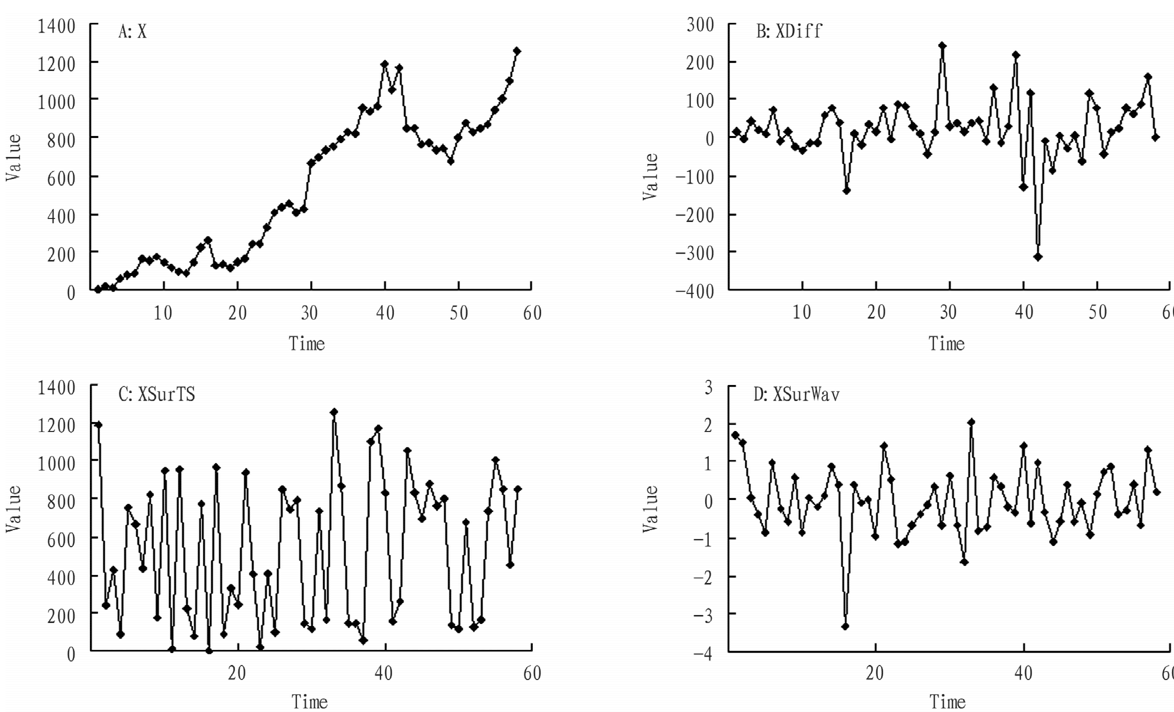


Fig. 1 Flowchart of *R/S* analysis of forest biological disasters in China based on R software

2.2.1 Method of unit root test. Non-stationary time series would exhibit obviously trends or periodicity[33]. Applied time series were generally results of a variety of intertwined factors, and thus, most of them were non-stationary; non-stationarity reflects the nature of the real world[34]. The unit root of a time series would affect the reliability of *R/S* analysis[18]. If a given time series is stationary, then it has no unit root. The unit root test was carried out by conducting an Augmented Dickey-Fuller (ADF) test through function of urdfTest provided by the library of fUnitRoots[35].

2.2.2 Methods of generating surrogate data. If a time series is non-stationary, *i.e.*, has a unit root, it should be transformed into stationary in order to eliminate its trend and periodicity for *R/S* analysis. Either the difference method[34] or surrogate method[36] could be employed. The core idea of the surrogate method was to eliminate non-linear correlation by reconstructing the power spectrum, while maintaining the same linear feature as seen in the original data[37]. Two different types of surrogate data were generated through 1) the function of surrogate in the library of tseries[38], and 2) the function of SurrogateData in the library of WaveletCo[39], and were assigned name XSurTS and XSurWav, respectively. Surrogate data were also tested against the unit root tests. The surrogate function could eliminate temporal dependencies and while maintaining the histogram of the original time series[37]. The SurrogateData function provided many methods such as white-noise for generating surrogate data[39].

2.2.3 Methods of estimating the Hurst index. While *R/S* analysis is very popular and widely used in various applications, there are many methods available in the literature for estimating the Hurst index, such as the periodogram regression method[40], the Higuchi method[41], modified *R/S* analysis[42], the ARFIMA estimation by exact maximum likelihood[43], multi-affine analysis[44], the variance method[45], the Whittle estimator and the wavelet based estimators[46], and detrended analysis[47]. Chen *et al*. (2006)[48] and Jiang and Deng (2004)[18] summarized equations of the above-mentioned methods besides the *R/S* analysis. In order to appraise the reliability of the analysis of the long-range dependence in the FBDs in China, this paper first employed *R/S* analysis, and then three functions of DFA, RoverS, HurstACVF in library fractal[49], to estimate and to compare the Hurst indices of the given time series. The algorithm of *R/S* analysis described by Chen (2010)[50] was followed, which could be thought of as a differencing procedure. For a given time series, first, calculate the differences, which means the ratio of increase or decrease; and then calculate the range R, the standard deviation S and their ratio *R/S*, corresponding to different time lag t. If there is a power law distribution between the ratio *R/S* and the time lag t, or there exists an equation $(R/S)t = A\ (t/2)^H$, then call the exponent *H* the Hurst index. When this equation is transformed into a double logarithm log-log relation, the slope of the linear function is the Hurst index. The closer the coefficient A is to 1, the more reliable the *R/S* analysis is[50]. The functions of DFA, RoverS, and HurstACVF are provided with library fractal[49] for detecting long-range dependence in time series, which all accept the time series data (original or surrogate) as an input parameter. Detrended Fluctuation Analysis (DFA) supports such methods as the use of a polynomial and a bridge to detrend the data, with poly1 as the default method. The RoverS estimates the Hurst coefficient by the *R/S* method, which runs like this: the series is partitioned into *m* groups, the number of groups is increased, and the calculation is repeated. A log-log plot of *R/S* versus number of groups is, ideally, linear, with a slope related to the Hurst index. The HurstACVF estimates the Hurst index by regression of a scaled asinh plot of autocovariance function (ACVF) of input time series versus log (lag), over intermediate lag values.



Note: *X*, the original time series of occurrence area data of FBDs in China during the period 1950 – 2007; XDiff, the differential sequence; XSurTS and XSurWav, two different types of surrogate data.

Fig. 2 Time series of area data, and its differential and surrogate series of forest biological disasters in China (X, XDiff, XSurTS, XSurWav are the same as in Table 1)

3 Results

3.1 Stationarity The original time series *X* (Fig. 2A) demonstrated a long-term increasing trend over time, while differential data (XDiff, Fig. 2B) and two different types of surrogate data (XSurTS and XSurWav, Fig. 2C, 2D) did not have obvious trends. From visual assessment, *X* was non-stationary; while XDiff, XSurTS and XSurWav, were stationary. The results of the unit root test (Table 1) showed that, *X* had a unit root, was non-stationary, and had an obvious trend; while each of XDiff, XSurTS and XSurWav, did not have a unit root, were stationary and did not have a trend. Therefore, the process of *R/S* analysis eliminated the trend in the original time series by differencing. The function of surrogate in the library tseries[38], and the function of SurrogateData in library Wavelet Co[39], generated stationary surrogate data of XSurTS and XSurWav, respectively.

Table 1 Results of unit root test on a time series of occurrence area data and its differential and surrogate series of forest biological disasters in China

Data	p-value	Have unit root	Stationary
X	0.2367	yes	no
XDiff	9.19E-11	no	yes
XSurTS	5.58E-05	no	yes
XSurWav	1.60E-12	no	yes

Note: X is the original time series; XDiff is its differential series; XSurTS and XSurWav are its surrogate series generated by function surrogate in library tseries and function SurrogateData in library WaveletCo of software R, respectively.

3.2 Hurst index

3.2.1 *R/S* analysis. The results of *R/S* analysis showed (Table 2) that, the Hurst index of time series of area data of FBDs in China during the period 1950 – 2007 was 0.6416 and greater than 0.5, indicating there was long-range dependence in the FBDs in China, and this was a persistent process indicating the spatial extent of FBDs would be expected to increase in the future. The results of *R/S* analysis showed (Table 2) that, the fitting of log-log linear model was significant (Multiple R-Squared = 0.9390, p = 0.0000), and the coefficient A of the corresponding power law model was approximately 1. Thus the model of *R/S* analysis was reasonable and acceptable. In order to visually appraise the validity of *R/S* analysis[50], the scatter plot of the data used in fitting the log-log linear model was created (Fig. 3). The time series roughly broke at about log ($t/2$) = 2 (or the year of 1963), and piecewise linear fitting was then performed. The results showed that, the Hurst indices, or the slopes of the linear models in Fig. 3, increased from 0.8469 to 0.8664. The time series could be fitted piecewise and the Hurst indices were all greater than 0.5.

Table 2 Results of *R/S* analysis of forest biological disasters in China

Item	Subitem	Value	Calculation
Hurst index H		0.6416	
	Multiple R-Squared	0.9390	
	Adjusted R-Squared	0.9379	
	p-value	0.0000	
	Constant H0 of linear model	0.0309	
	Coefficient A of power law model	1.0314	$(R/S)t = A(t/2)^H$

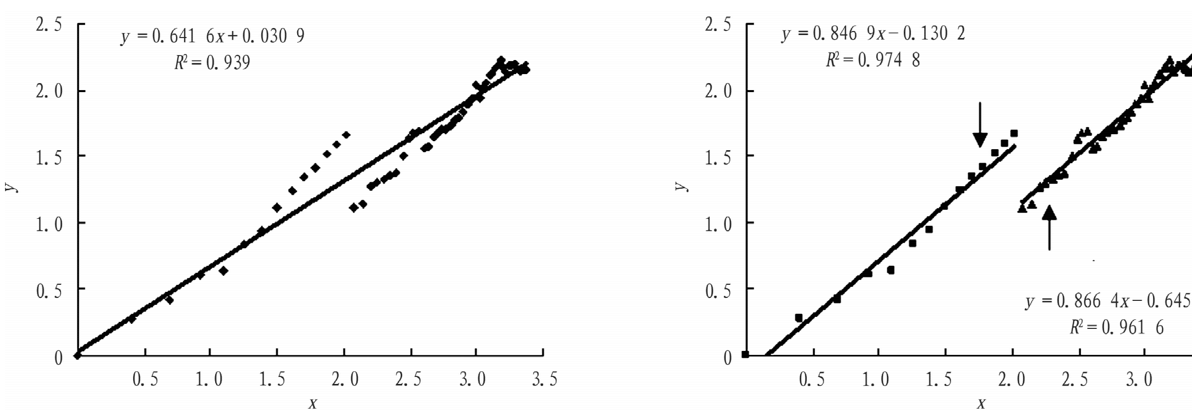


Fig. 3 Log-log plot of $x(t/2)$ – $y(R/S)$ data used in *R/S* analysis of forest biological disasters in China

3.2.2 DFA, RoverS and HurstACVF analysis. The DFA, RoverS and HurstACVF analysis showed that: 1) the Hurst indices calculated using these three methods with X as input parameter were greater than 0.5 (except for DFA with XSurWav); 2) the DFA method was sensitive to the input parameter, and its output was unstable. Only the Hurst index calculated with the DFA method with XSurWav as input parameter was less than 0.5, while the Hurst indices with other combinations were all greater than 0.5, and were relatively close to each other; 3) the Hurst indices of the surrogate data XSurTS were comparatively stable among different methods. This could probably be explained by its surrogate algorithm which was time series-oriented and maintained most of the characteristics of the original time series; 4) the Hurst index calculated with the *R/S* analysis was somewhat conservative. In short, the Hurst indices from these three different methods supported the conclusions from the *R/S* analysis that, a long-range dependence existed in the time series of occurrence area data of FBDs in China, or, since this increase was a persistent process the spatial extent of FBDs is expected to increase in the future. All four estimation methods quantitatively supported the qualitative visual assessment seen in Fig. 2A.

4 Discussions and conclusions

4.1 *R/S* analysis and estimation of Hurst index Jiang and Deng (2004) suggested that, when calculating the Hurst index using the *R/S* analysis, several factors should be considered: 1) the effects of trend or periodicity; 2) the validity test of the Hurst index when it is found to be about 0.5; 3) the effects of sample size (larger is better). 4) the reasonable scale range to fit the linear model; Otherwise, the reliability of the results would be somewhat affected. This paper took these into consideration, and adopted different estimation methods for comparison. The effects of trend or periodicity, or stationarity, could be tested by a unit root test. The difference method or the surrogate method could effectively eliminate trend and periodicity of non-stationary time series. Eliminating trend and periodicity by differencing was thought of as a weakness of ARMA model when analyzing and forecasting time series[34], while in the process of the *R/S* analysis, which was carried out on differential time series, it was helpful to enhance the robustness and reliability of the results. This paper also found that the differential series was stationary (Table 1, Fig. 2B). There were no generally accepted validity test method of determining whether the significance level of the computed measure of Hurst index was statistically different from 0.5[18]. Among others, for instance based on the Monte Carlo method proposed by Weron (2002)[51] and by Turvey (2007)[52], the use of a randomly reordered test was the common method used to detect the validity of *R/S* analysis[4]. It was assumed that the randomly reordered time series was a random sequence, and its Hurst index should be equal to 0.5 according to the definition of the indicator[11]. In a study of the trend of vegetation dynamics in the Qinghai-Tibet Plateau using Hurst indices, Peng *et al.* (2012) found that the Hurst indices of randomly reordered time series were closer to 0.5 than the original data, centering on the value of 0.55. Chen *et al.* (2006) estimated ten kinds of normally used probability sequences by employing seven different methods, and found that these seven methods were all able to detect random non-long-range correlated sequences, with all Hurst indices falling into 0.45 – 0.55. As for the confidence limits generated by the Monte Carlo method, Turvey (2007) observed that they were also approximations, and were determined independently of the drift and volatility of the underlying stochastic process; *i.e.* two researchers could not use differences in either drift or volatility to explain differences in their estimates of Hurst indices. The significance level was usually chosen to be one over the square root of the sample length; however, it was noted that for small sample size n, there was a significant deviation from the 0.5 slope[21, 51]. Anis and Lloyd and afterwards Peters introduced a new formulation to improve the performance for a small n[7, 21, 51]. While Sánchez-Granero *et al.*, (2008) found that, for some random series, the Hurst index was higher than 1, which made no sense. Therefore, to summarize and simplify, this paper adopted the interval of 0.45 – 0.55 for empirical validity test of the Hurst index, which meant that, if the Hurst index fell into the interval of 0.45 – 0.55, it indicated that the Hurst index was 0.5, *i.e.* the time series reflected an ordinary Brownian motion, and the process was not persistent; if the Hurst index was greater than 0.55, the process was persistent or exhibited autocorrelation, and the closer the Hurst index came to the value 1, the stronger the persistence or autocorrelation. Also, if the Hurst index was less than 0.45, the process was anti-persistent or anti-correlation, and the closer the Hurst index came to the value 0, the stronger the anti-persistence. In short, if the Hurst index was not 0.5, then the time series reflected a fractal Brownian motion, which meant there existed varying degrees of autocorrelation and long-range dependence in the corresponding process[17, 50]. Although larger sample sizes were generally considered to be better[18], in practice, some research needs to be carried out on short data sets. For example, Weron and Przybylowicz (2000) estimated the Hurst index using 670 daily returns of the spot electricity price in California, while Taqqu *et al.* (1995)[53] based their statistical conclusions on 50 simulated trajectories of fractal Brownian noise or FARIMA. Furthermore, the sample length of the application in forestry and ecology was much shorter. For instance, it was 22 in the research study conducted by Peng *et al.* (2012) to quantify the consistency of vegetation dynamic trends in the Qinghai-Tibet Plateau after the study period of their research. From the viewpoint of statistics, a sample is considered large when the sample size exceeds 50 (or at least greater than 30). The sample size of this study was 58, and was large enough. Despite the fact that the sample sizes were not large, the results of Peng *et al.* (2012) and others were satisfactory. On one hand, it was probable the *R/S* analysis revealed the evolutionary characteristics of a dynamical system throughout its time series, which were determined independently of the drift and volatility of the underlying stochastic process[52]. Alternatively, if the sample size was too small, say 4, other methods would be preferable to analyze the characteristics of a time series. Based on the grey system theory, Wang *et al.* (2007)[54] constructed effectively GM (1, 1) grey models using a series of five surveys of the national Continuous Forest Inventory in China during the period 1973 – 1998 (the national Continuous Forest Inventory is conducted in China once every five years), and satisfactorily analyzed and forecasted the dynamics of forest biodiversity in China. As to the reasonable scale range to fit the linear model[18], it could be determined effectively with the help of a scatter plot. The more the data points and its trend line matched, the more reliable the *R/S* analysis was[50]. The *R/S* analysis was developed based on simple statistics without complex assumptions related to the underlying process of the time series, worked well in many cases, and was the most popular in various applications. As far as the estimation algorithm was concerned, researchers haven't yet agreed on a single method. Each method had its drawbacks and no single estimator has been found to be suitable in all cases. For more detailed discussions, see Robinson (2003)[55]. To further analyze the reliability of the Hurst index, estimation methods other than the *R/S* analysis should be conducted for comparison, including the surrogate method. The results of this study (Table 1, Fig. 2) demonstrated that, the surrogate method could effectively eliminate trend and periodicity of a time series[36], thus was an alternative method of estimating the Hurst index[37]. Also, there were slight differences between the Hurst indices that were calculated by combinations of the estimation method and surrogate data generated from different surrogate algorithms (Table 3). The results of this study also showed that, the quality of the surrogate data generated by the function of surrogate in the library of tseries[38] using R software was considerably better, maintaining consistency between different estimation methods of the Hurst index. The function of DFA in the library of fractal[49] was sensitive to input data, and the results were somewhat unstable. It is well known and accepted that some human and natural phenomena show long memory and a wide variety of papers discuss this topic as it relates to the natural sciences[7]. Fractal theory is effective for modeling complex physical process and dynamical system by searching for the simple process that underlies those systems, and thus allows researchers to reveal the hidden regularity, hierarchy and scale invariance of complex natural and social phenomena. Since stationarity is an idealized hypothesis and non-stationarity is the nature of the real world[34], fractality might be the nature of most applied time series. Therefore, even though some time series might not meet the ideal mathematical requirements of *R/S* analysis, the fractality of the study dynamical system still warranted satisfactory results.

Table 3 Hurst indices of area data series of forest biological disasters in China

Input parameter	Estimation method			
	R/S	DFA	RoverS	HurstACVF
X	0.6416	0.9697	0.7833	0.8627
XSurTS		0.9159	0.6028	0.8954
XSurWav		0.3401	0.7676	0.7595

Note: Input parameters of X, XSurTS, XSurWav are the same as in Table 1. Methods of DFA, RoverS, HurstACVF, provided by R software.

4.2 FBDs in China and its long-range dependence FBD are important forms of natural disasters and are major disturbing factors to forest ecosystems, which impose heavy impacts on the energy flow and material cycling of forest ecosystems[2]. Among natural disasters, biological disasters characteristically have various forms, high frequency, and wide distribution and create huge losses for humans[1]. FBDs are among the prominent problems involved in the national economic and social development of China, which seriously damage forest resources, natural landscapes and living environments, and constrain multi-functions and multi-values of natural ecology[3, 56]. Monitoring and controlling harmful forest organisms is an important part of forestry work and is important as it relates to the management and control of national public resources[1]. The results of this study showed that the Hurst index of the time series of occurrence area data caused by FBDs in China was greater than 0.5, which quantified the long-range dependence in the FBDs in China. In other words, the change of occurrence area of FBD was positively auto correlated, and the trend of spatial increase in the study period indicated a persistent tendency in the future. In short, the trend of FBDs in China continues to worsen, which was consistent with the findings and inferences of Gu *et al.* (2004), Yan and Chai (2006), and Wei *et al.* (2013). A variety of factors led to FBDs. This results of piecewise linear fitting (Fig. 3) showed that the Hurst indices increased from 0.8469 to 0.8664, which indicated that 1) there was long-range dependence in the time series of occurrence area data of FBDs in China and 2) there was probably non-periodic mutation at about the year 1963, which explained the formation of two different time series of FBDs in China before and after this year. The mutation could probably be explained by "the Great Leap Forward" in 1958 and later "the three years of difficulty and natural disasters" in China. Climate change and environment degradation were important factors causing increased frequencies and intensities of FBDs[1-3]. Increased domestic and foreign trade, which provides a vector for the invasion and proliferation of harmful forest organisms, inadvertently results in a worsening of the frequency and intensity of FBDs. Furthermore, these factors all created conditions favorable to FBD occurrences. As a result additional areas need to be monitored for outbreaks of FBDs. This aggravates the task of monitoring and controlling FBDs through the increased spatial coverage of forest resources and new plantations[1]. Increased occurrences of FBDs also aggravate the damages done to forest biodiversity and the fragile environment caused by increased demands of forest products by the growing population and expanding economic development, and is especially complicated by previous mismanagement of the nation's forest[3]. China is developing a low carbon economy and tackling climate change, in order to construct China's Three Systems in forestry and to realize China's strategic target of Two Increases in forestry by the year of 2020. Basic FBD research should be strengthened, monitoring and control of harmful forest pests should be reinforced, forest health programs promoted, development and protection of forest resources be equally emphasized. Also, research related to and implementation of a regional forestry development strategy should be emphasized, and the nation's forest resources monitoring system be improved and ameliorated from a strategic perspective.

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