



## Article

# Quantifying Influences of Natural and Anthropogenic Factors on Vegetation Changes Based on Geodetector: A Case Study in the Poyang Lake Basin, China

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**Abstract:** Understanding the driving mechanism of vegetation changes is essential for vegetation restoration and management. Vegetation coverage in the Poyang Lake basin (PYLB) has changed dramatically under the context of climate change and human activities in recent decades. It remains challenging to quantify the relative contribution of natural and anthropogenic factors to vegetation change due to their complicated interaction effects. In this study, we selected the Normalized Difference Vegetation Index (NDVI) as an indicator of vegetation growth and used trend analysis and the Mann-Kendall test to analyze its spatiotemporal change in the PYLB from 2000 to 2020. Then we applied the Geodetector model, a novel spatial analysis method, to quantify the effects of natural and anthropogenic factors on vegetation change. The results showed that most regions of the basin were experiencing vegetation restoration and the overall average NDVI value in the basin increased from 0.756 to 0.809 with an upward yearly trend of +0.0026. Land-use type exerted the greatest influence on vegetation change, followed by slope, elevation, and soil types. Except for conversions to construction land, most types of land use conversion induced an increase in NDVI in the basin. The influence of one factor on vegetation NDVI was always enhanced when interacting with another. The interaction effect of land use types and population density was the largest, which could explain 45.6% of the vegetation change, indicating that human activities dominated vegetation change in the PYLB. Moreover, we determined the ranges or types of factors most suitable for vegetation growth, which can be helpful for decision-makers to optimize the implementation of ecological projects in the PYLB in the future. The results of this study could improve the understanding of the driving mechanisms of vegetation change and provide a valuable reference for ecological restoration in subtropical humid regions.

**Keywords:** Poyang Lake basin; NDVI; climate change; human activities; Geodetector



**Citation:** Wang, Y.; Zhang, Z.; Chen, X. Quantifying Influences of Natural and Anthropogenic Factors on Vegetation Changes Based on Geodetector: A Case Study in the Poyang Lake Basin, China. *Remote Sens.* **2021**, *13*, 5081. <https://doi.org/10.3390/rs13245081>

Academic Editors: Francesco Pirotti, Monika Moskal, H. Jaime Hernández Palma, Gaia Vaglio Laurin and Erico Kutchartt

Received: 18 November 2021

Accepted: 11 December 2021

Published: 14 December 2021

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## 1. Introduction

Vegetation, as a major part of the terrestrial ecosystem, plays a crucial role in climate regulation, carbon cycle, wind and sand fixation, soil and water conservation, and hydrologic processes [1–4]. Vegetation is a sensitive indicator that reflects regional and global environmental change [5]. Thus, monitoring vegetation changes and exploring their driving forces can improve the understanding of surface processes and the interaction between vegetation and the atmosphere, and provide references for formulating ecological protection policies and optimizing land use management [6–8].

The Normalized Difference Vegetation Index (NDVI) is an important indicator that reflects the status of vegetation growth [9,10]. It is one of the most commonly used

vegetation indexes and has been widely applied in monitoring vegetation change in recent years due to the rapid development of high resolute satellite-derived NDVI datasets [11,12]. The widely used satellite-derived NDVI datasets mainly include the Global Inventory Monitoring and Modeling System (GIMMS) NDVI, the System Probatoire d'Observation de la Terre (SPOT) NDVI, and Moderate Resolution Imaging Spectroradiometer (MODIS) NDVI with a spatial resolution of 8 km, 1 km, and 250 m to 1 km respectively [13–15]. Tian et al. [13] indicated that the platform/sensor change of GIMMS NDVI and SPOT NDVI may result in misleading data regarding vegetation changes. In addition, the GIMMS NDVI datasets perform poorly in humid regions. In contrast, MODIS NDVI datasets based on a single sensor are not affected by platform/sensor shift, which maintains data consistency. Due to high data quality and moderate spatiotemporal resolution, the MODIS NDVI datasets have been widely used in research of vegetation change [16–20]. Compared to these three main NDVI datasets, the Landsat datasets have a higher spatial resolution (30 m). However, long rainy days and high cloud cover during the summertime may affect the acquisition of clear Landsat scenes in humid regions [21]. Therefore, in this study, we selected the MODIS NDVI product as an indicator to investigate vegetation change in humid regions.

Vegetation changes can be influenced by various natural and anthropogenic factors [22,23]. Climate change mainly exerts influence on ecosystems through the change of temperature and precipitation, which could affect the rates of plant photosynthesis, respiration, and soil organic carbon decomposition, thus influencing the productivity of vegetation ecosystems [7,24]. In addition, solar radiation is also an important factor influencing vegetation growth [25,26]. Hydrothermal conditions and nutrient conditions vary across topographic conditions and soil types, which exert great influences on vegetation growth [17,18]. With the development of science and technology and rapid population growth, human interferences with the ecosystem have become more intensive, which significantly affect vegetation growth. For example, economic development and rapid urbanization could lead to vegetation degradation by compressing the space of vegetation growth [27–29]. Overgrazing and deforestation are considered the dominant driving force of grassland and forest degradation respectively [30,31]. Meanwhile, reasonable human activities, for example, large-scale ecological restoration programs implemented in China have dramatically changed the landscape and effectively alleviated the adverse effects of climate variation, which is beneficial to vegetation growth [6,32,33]. Vegetation changes are also closely related to many other factors include the CO<sub>2</sub> fertilization effect, nitrogen deposition rate, and extreme weather events [25,34,35]. The vegetation change is a complicated process due to the interaction effect of natural and anthropogenic factors, which make it challenging to quantitatively evaluate the contribution of different factors to vegetation change [7,16].

The driving mechanisms of vegetation change have attracted extensive attention, and many methods have been developed to explore the driving forces of vegetation change. Correlation and regression analysis are the two most commonly used methods to analyze the relationship between climatic factors and vegetation change. For instance, Gu et al. [36] investigated the response of vegetation change to climate change in the Red River basin during 2000–2014 based on the partial correlation and regression analysis. Zhang, et al. [37] applied correlation and regression analysis to study vegetation change and its relationship with climate and human factors in the Yangtze River basin from 1982 to 2013. In recent years, quantifying the contributions of climate change and human activities to vegetation change has become a crucial topic of global change. For instance, Qu, et al. [22] utilized the residual analysis method to investigate the effects of climate change and human activities on vegetation change in the Yangtze River basin from 1982 to 2015. Leroux, et al. [12] adopted the random forest algorithm to quantify the relative contribution of natural and human factors to vegetation change in the Sahel from 2000 to 2015. However, most of the previous research took the natural and anthropogenic factors as independent while ignoring their interaction effect on vegetation change. In addition, the traditional statistical

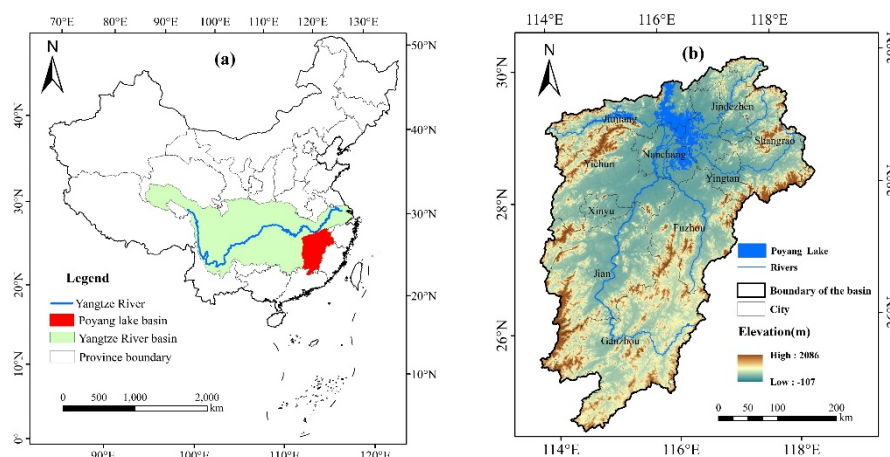
methods, for example, correlation and regression analysis assume that the relationships between vegetation change and its driving factors are linear. However, this kind of linear relationship may not exist due to the complicated interaction between natural and human factors [38]. Due to the interaction, the relative influences of factors on vegetation can be enhanced and their relationship with vegetation change can be changed, which means that the analysis of the driving force of vegetation change based on the linear assumption may be biased [18,20,39]. The Geodetector model is a new statistical method to detect spatial heterogeneity and explore its driving mechanism [38]. Its core assumption is that the dependent variable has a similar spatial pattern with the independent variable that has an important influence on it [40]. One major advantage of this method is that it can detect the interaction of two driving factors on dependent variables and don't have to follow the linear assumption of traditional statistical methods [38]. In recent years, it has been successfully employed to explore the driving force in many fields such as vegetation change [17], land-use change [41], soil erosion [42], and landslides [43].

The Poyang Lake basin (PYLB) is a typical subtropical humid region, which plays a crucial hydrological and ecological role in the middle and lower reaches of the Yangtze River [21,44]. In recent decades, multiple ecological restoration programs such as the "Grain To Green Program" have been implemented in this basin [21]. Meanwhile, this basin is experiencing rapid economic development and urbanization [45]. Under the context of these anthropogenic activities coupled with climate change, the vegetation coverage has undergone dramatic change in the PYLB. Although some studies have analyzed vegetation change and its causes in recent years [21,46,47], few researchers have addressed the interaction effect of different potential driving factors on vegetation change in the PYLB. The relative contribution of different natural and anthropogenic factors and their interaction effect on vegetation changes remain unclear. Therefore, in this study, we selected the NDVI as an indicator and used the Geodetector model to explore the influences of natural and anthropogenic factors on vegetation change in the PYLB. The objectives of this study are as follows: (1) to evaluate the spatial pattern and dynamic of vegetation NDVI in the PYLB; (2) to distinguish the relative contribution of natural and anthropogenic factors to the NDVI changes and identify the dominant factor; (3) to explore the interaction effects of factors on the NDVI change. This study can improve our understanding of the driving mechanism of vegetation change in subtropical regions and provide references for vegetation restoration in the PYLB.

## 2. Materials and Methods

### 2.1. Study Area

The Poyang Lake basin (24°24' N–29°46' N, 113°23' E–118°46' E), located in the middle-lower region of the Yangtze River basin, has a catchment area of  $1.62 \times 10^5$  km<sup>2</sup> [48]. It consists of the Poyang Lake region and five major tributaries namely the Ganjiang river, Fuhe river, Raohe river, Xinjiang river, and Xiushui river (Figure 1). This basin is surrounded by mountains in the east, south, and west and the Poyang Lake region is relatively low-lying. The climate in this basin is typically subtropical monsoon climate. The mean annual temperature is approximately 17.6 °C and the mean annual precipitation is approximately 1680 mm [46]. This basin is rich in natural resources due to great hydrothermal conditions and the forest is the dominant land-use type [21].



**Figure 1.** (a) Location of the Poyang Lake basin in China, and (b) the digital elevation model (DEM) of the basin.

## 2.2. Data Sources

The MOD13Q1 NDVI product with a spatial resolution of 250 m covering the study area for the period of 2000–2020 was obtained from (<https://ladsweb.modaps.eosdis.nasa.gov> accessed on 23 May 2021). We adopted the max value composites (MVC) method to composite the annual NDVI value of 2000–2020 [49]. To better analyze the vegetation dynamics, we divided the NDVI into five grades, namely low vegetation coverage [0, 0.2), low to moderate vegetation coverage [0.2, 0.4), moderate vegetation coverage [0.4, 0.6), moderate to high vegetation coverage [0.6, 0.8) and high vegetation coverage [0.8, 1] [17].

The digital elevation model (DEM) data with a spatial resolution of 90 m was downloaded from the Geospatial Data Cloud (<http://www.gscloud.cn/> accessed on 23 May 2021). The elevation, slope, and aspect were derived from the DEM data using ArcGIS 10.2 (ESRI, Redlands, CA, USA). The meteorological dataset including monthly mean temperature and precipitation during 2000–2020 were collected from the National Meteorological Information Center (<http://data.cma.cn/> accessed on 23 May 2021). The ANUSPLIN 4.2 software was used to interpolate raster-gridded meteorological data. Then the Raster Calculator tool of ArcGIS was used to calculate the annual precipitation and mean annual temperature. The population density data from 2000 to 2020 with a spatial resolution of 1 km was collected from (<https://www.worldpop.org/> accessed on 23 May 2021). Land use data with a spatial resolution of 1 km in 2000 and 2020 were collected from the Center for Resources and Environment of the Chinese Academy of Sciences (<https://www.resdc.cn/> accessed on 23 May 2021). Six primary classes of land use types (cropland, forest, grassland, water area, construction land, and unused land) were included. The soil type data with a spatial resolution of 1 km and main road (highway and railway) data were also obtained from (<http://www.resdc.cn/> accessed on 23 May 2021). The Spatial Analysis tool in ArcGIS was used to generate the buffer of the distance to main roads. All the data were resampled into the resolution of 250 m.

## 2.3. Methodology

The methodology framework of the research was shown in Figure 2.

### 2.3.1. Trend Analysis

In this study, we adopted the linear regression model and Mann-Kendall test statistic to detect the trends of vegetation NDVI and climate factors (annual mean temperature and precipitation) and their statistical significance from 2000 to 2020 at the pixel scale [50]. The

Mann-Kendall test has been widely adopted in research of vegetation change [51]. The slope coefficient of the pixel-level trend was calculated based on the following formula:

$$\text{Slope} = \frac{t \times \sum_{i=1}^t (i \times \text{Var}_i) - (\sum_{i=1}^t i) (\sum_{i=1}^t \text{Var}_i)}{t \times (\sum_{i=1}^t i^2) - (\sum_{i=1}^t i)^2} \quad (1)$$

where  $t$  represents the total number of years of the study period, and  $i$  represent the serial number of the year.  $\text{Var}_i$  represents the research variable in the year  $i$ .  $\text{Slope} > 0$  represents that the variable is increasing and vice versa.

The Mann-Kendall test based on the test statistic  $S$  defined as:

$$S = \sum_{i=1}^{t-1} i \sum_{j=i+1}^t \text{sign}(\text{NDVI}_i - \text{NDVI}_j) \quad (2)$$

$$\text{sign}(\text{NDVI}_i - \text{NDVI}_j) = \begin{cases} -1 & \text{if } (\text{NDVI}_i - \text{NDVI}_j) < 0 \\ 0 & \text{if } (\text{NDVI}_i - \text{NDVI}_j) = 0 \\ 1 & \text{if } (\text{NDVI}_i - \text{NDVI}_j) > 0 \end{cases} \quad (3)$$

the variance of  $S$  is:

$$\text{Var}(S) = \frac{t(t-1)(2t+5)}{18} \quad (4)$$

The statistics  $Z$  is defined as:

$$Z = \begin{cases} \frac{S-1}{\sqrt{\text{Var}(S)}} & S > 0 \\ 0 & S = 0 \\ \frac{S+1}{\sqrt{\text{Var}(S)}} & S < 0 \end{cases} \quad (5)$$

Based on a confidence level of 0.05 in the Mann-Kendall test, if  $|Z| \geq 1.96$ , the trend is significant. Furthermore, based on the linear regression analysis and Mann-Kendall test, we divided the NDVI change into five grades, namely significant restoration (slope  $> 0$ ,  $|Z| \geq 1.96$ ), slight restoration (slope  $> 0$ ,  $|Z| < 1.96$ ), stable (slope = 0), slight degradation (slope  $< 0$ ,  $|Z| < 1.96$ ) and significant degradation (slope  $< 0$ ,  $|Z| \geq 1.96$ ) [52].

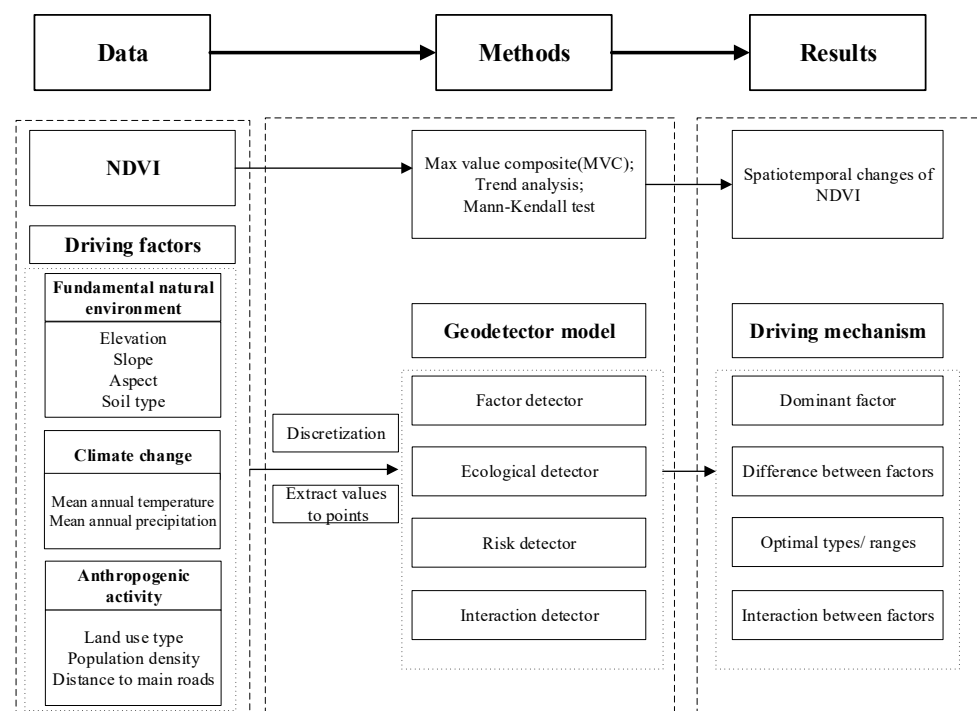


Figure 2. The methodology framework of this study.

### 2.3.2. Factors Selection

Both natural and anthropogenic factors can significantly exert an influence on vegetation growth. In this study, the NDVI was selected as an indicator of vegetation growth, and nine natural and anthropogenic factors were selected from the respects of the fundamental natural environment, climate change, and human activity (Table 1). Fundamental natural elements such as elevation, slope, aspect, and soil types can significantly affect the evapotranspiration and water use efficiency of vegetation, thereby affecting vegetation growth [11,12]. Temperature and precipitation are considered the most important climatic factors that affect vegetation [53,54]. Anthropogenic activities such as land-use type, population density, and distance to main roads can dramatically affect the space of vegetation growth [16,18].

**Table 1.** Influencing factors of vegetation change.

Categories	Factors	Code	Unit
Fundamental natural environment	Elevation	X1	m
	Slope	X2	degree
	Aspect	X3	categorical
	Soil type	X4	categorical
Climate change	Mean annual precipitation	X5	mm
	Mean annual temperature	X6	°C
Anthropogenic activity	Land-use type	X7	categorical
	Population density	X8	people/km <sup>2</sup>
	Distance to main roads	X9	km

The Geodetector software can only deal with discrete variables [38]. Thus, all factors selected were converted into discrete formats (Table 2). In this study, elevation, mean annual precipitation, mean annual temperature was divided into 6 categories based on the natural breakpoint method in ArcGIS 10.2 [17]. The slope was divided into 6 categories based on the Technical Regulations for Land Use Status Survey [18]. The aspect, population density, and distance to main roads were divided into 9, 6, and 6 categories respectively based on professional knowledge and previous research [18]. The soil type and land-use type were reclassified into 9 and 6 categories based on the existing specifications, respectively. The spatial pattern of all nine reclassified factors was shown in Figure 3. We used the Create Fishnet function in ArcGIS to create a 3 km × 3 km regular grid to generate 18001 sample points. Then, we used the Extract Multi Values to Points function in ArcGIS to extract information of all variables based on the position of sample points to quantify the relationships between NDVI and potential driving factors [16].

**Table 2.** Grading standards of the potential driving factors for vegetation NDVI.

Categories \ Factors	Elevation m	Slope Degree	Aspect	Soil Type	Mean Annual Precipitation mm
1	−107–126	0–2	Gentle slope	Leached	1475.32–1683.01
2	126–265	2–6	North slope	Primary	1683.01–1843.23
3	265–433	6–15	Northeast slope	Semi-hydromorphic	1843.23–1979.71
4	433–652	15–25	East slope	Anthropogenic	1979.71–2116.19
5	652–984	25–35	Southeast slope	Ferralsol	2116.19–2312.02
6	984–2086	35–46	South slope	Urban	2312.02–2982.56
7			Southwest slope	Lakes and reservoirs	
8			West slope	Rivers	
9			Northwest slope	Islands	

Table 2. Cont.

Categories \ Factors	Mean Annual Temperature °C	Land-Use Type	Population Density Person/km <sup>2</sup>	Distance to Main Roads km <sup>2</sup>
1	9.23–14.47	Cropland	0–50	0–5
2	14.47–16.26	Forest	50–100	5–10
3	16.26–17.52	Grassland	100–200	10–20
4	17.52–18.46	Water area	200–300	20–30
5	18.46–19.31	Construction land	300–400	30–40
6	19.31–20.66	Unused land	>400	40–67

### 2.3.3. Geodetector Model

The Geodetector model is a new spatial statistic tool to explore spatial heterogeneity and quantitatively evaluate the contribution of driving factors [38]. It consists of four modules, namely factor detector, ecological detector, risk detector, and interaction detector.

(1) Factor detector. This module can quantitatively detect the extent to which a driving factor  $X$  can explain the spatial differentiation of vegetation NDVI through the value of  $q$  statistic:

$$q = 1 - \frac{\sum_{h=1}^L N_h \sigma_h^2}{N \sigma^2} \quad (6)$$

where  $q$  represents the explanatory power of a specific driving factor for NDVI;  $h$  is the stratification of the category number of driving factor  $X$ ;  $N_h$  and  $N$  are numbers of units for layer  $h$  and the whole region, respectively. The greater the value of  $q$ , the greater the explanatory power of the driving factor  $X$  on vegetation NDVI.

(2) Ecological detector. This module can determine whether there is a significant difference in the influence of the distribution of NDVI between the two driving factors ( $X_1$  and  $X_2$ ). It can be examined by  $F$  statistic:

$$F = \frac{N_{X_1} (N_{X_2} - 1) SSW_{X_1}}{N_{X_2} (N_{X_1} - 1) SSW_{X_2}} \quad (7)$$

$$SSW_{X_1} = \sum_{h=1}^{L_1} N_h \sigma_h^2 \quad (8)$$

$$SSW_{X_2} = \sum_{h=1}^{L_2} N_h \sigma_h^2 \quad (9)$$

where  $N_{X_1}$  and  $N_{X_2}$  are the sample number of two driving factors ( $X_1$  and  $X_2$ ), respectively;  $SSW_{X_1}$  and  $SSW_{X_2}$  are the sums of variance of each grade formed by two driving factors, respectively;  $L_1$  and  $L_2$  are the number of grades of driving factor  $X_1$  and  $X_2$ , respectively.

(3) Risk detector. This module can determine whether there is a significant difference in the mean value of NDVI between two ranges of a driving factor and determine the suitable range or type of each driving factor. It can be examined by  $t$  statistics:

$$t = \frac{\bar{Y}_{h=1} - \bar{Y}_{h=2}}{\left[ \frac{Var(Y_{h=1})}{n_{h=1}} + \frac{Var(Y_{h=2})}{n_{h=2}} \right]^{1/2}} \quad (10)$$

where  $\bar{Y}_h$  is the mean value of NDVI in the subzone  $h$ ;  $n_h$  is the number of samples in the subzone  $h$ ;  $Var$  is the variance.

(4) Interaction detector. This module can identify the interactive effect on the NDVI between two driving factors. First, the  $q$  values of two driving factors for NDVI were calculated ( $q(X_1)$  and  $q(X_2)$ ). Then, the  $q$  values of the interactive effect were calculated ( $q(X_1 \cap X_2)$ ) and compared with  $q(X_1)$  and  $q(X_2)$  to determine the interaction type between two driving factors (Table 3) [55].

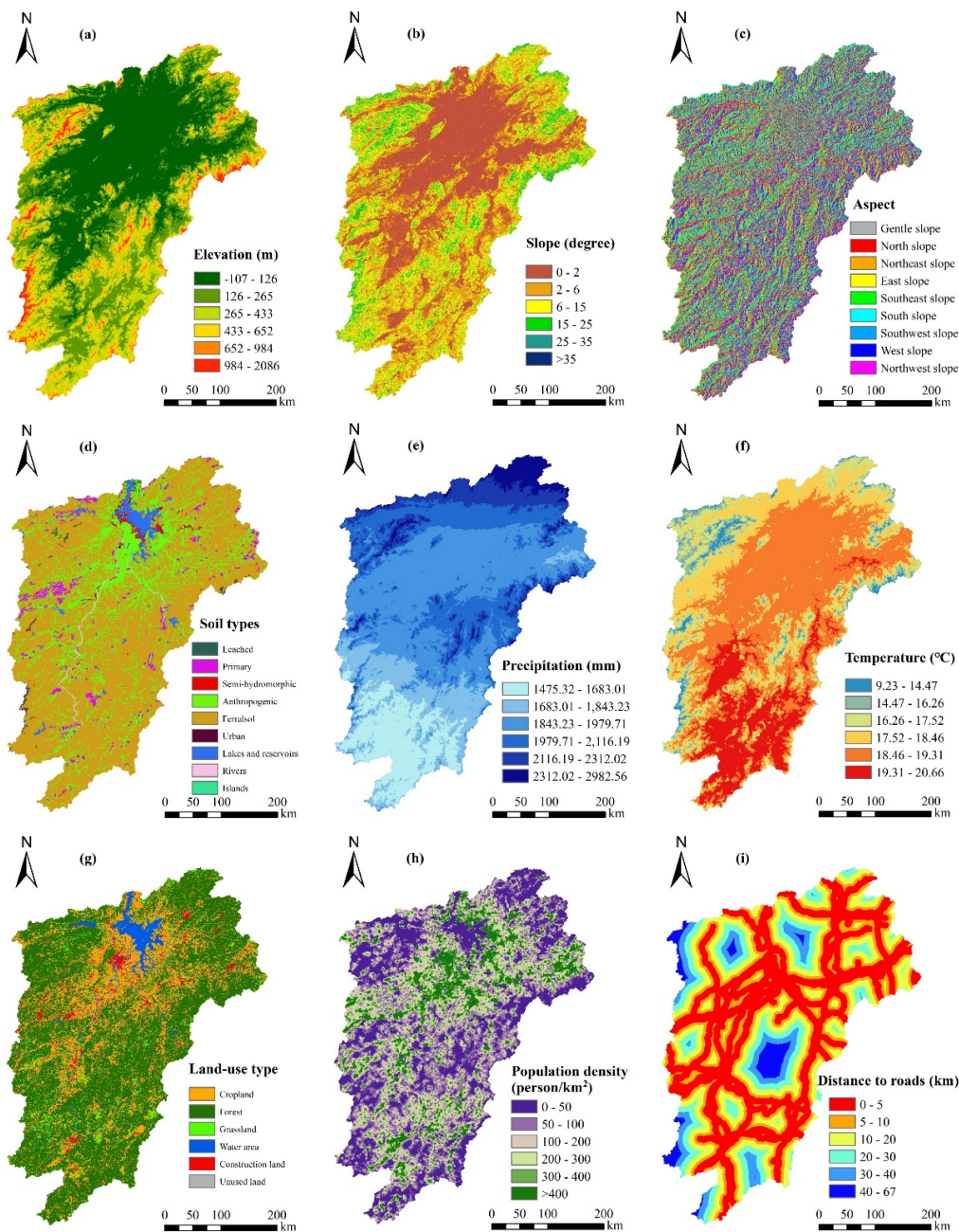


Figure 3. Spatial distributions of natural and anthropogenic factors in the PYLB in 2020.

Table 3. Definition of the interaction types in the Geodetector model.

Interaction Relationship	Interaction Types	Description
$q(X_i \cap X_j) < \min(q(X_i), q(X_j))$	Nonlinear-weaken	The impacts of single variables are nonlinearly weakened by the interaction of two variables.
$\min(q(X_i), q(X_j)) < q(X_i \cap X_j) < \max(q(X_i), q(X_j))$	Uni-variable weaken	The impacts of single variables are uni-variable weakened by the interaction of two variables
$q(X_i \cap X_j) = q(X_i) + q(X_j)$	Independent	The impacts of single variables are independent.
$\max(q(X_i), q(X_j)) < q(X_i \cap X_j) < q(X_i) + q(X_j)$	Bi-variable enhanced	The impacts of single variables are bi-variably enhanced by the interaction of two variables.
$q(X_i \cap X_j) > q(X_i) + q(X_j)$	Nonlinear-enhanced	The impacts of single variables are nonlinearly enhanced by the interaction of two variables.



### 3. Results

#### 3.1. Spatiotemporal Changes of the NDVI in the PYLB

The spatial pattern of vegetation NDVI showed apparent heterogeneity in the PYLB during the study period (Figure 4). In general, vegetation coverage is high in the mountain regions and relatively low in plain regions in the PYLB. The NDVI change was mainly manifested in the transformation of regions with moderate to high vegetation coverage to high vegetation coverage.

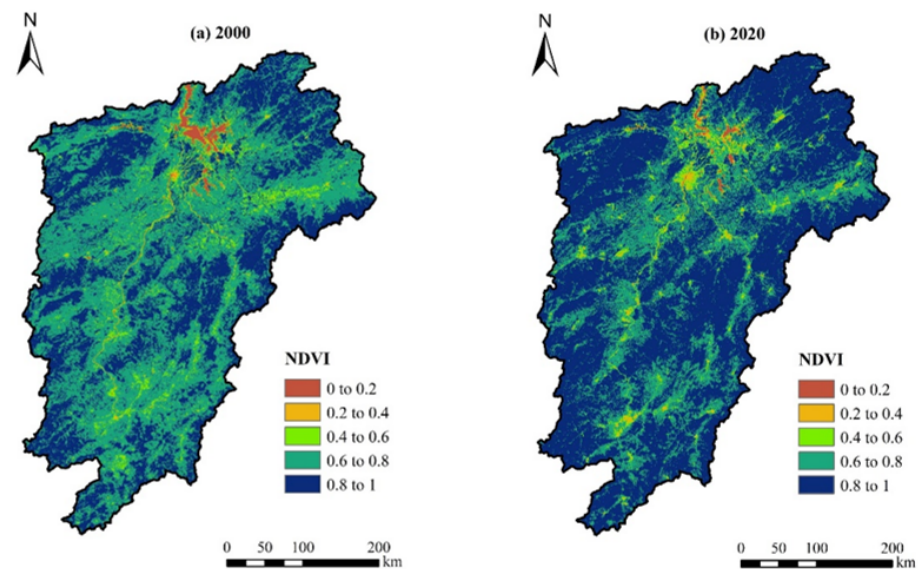


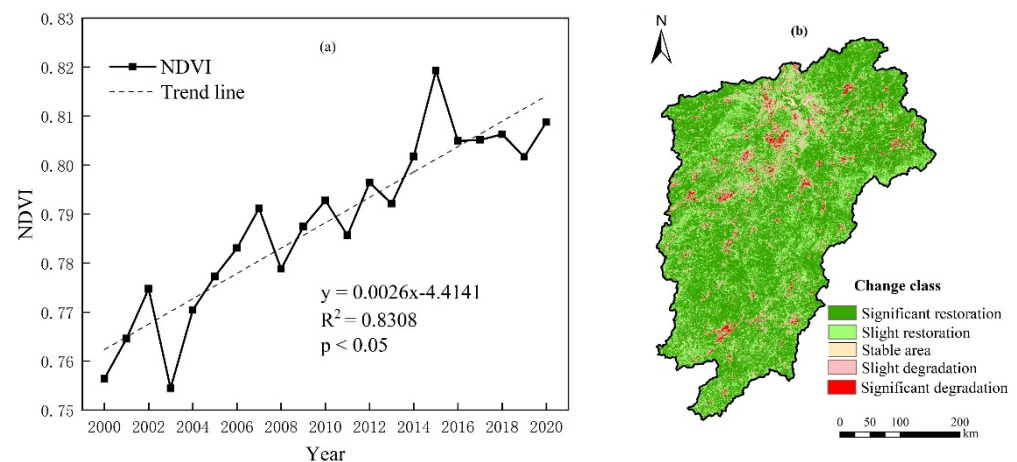
Figure 4. Spatial distributions of vegetation NDVI in the PYLB in 2000 and 2020.

Regions with moderate to high or high vegetation coverage collectively occupied approximately 93.41% and 94.71% of the PYLB in 2000 and 2020 respectively (Table 4). From 2000 to 2020, the proportion of the regions with high vegetation coverage has dramatically increased by 25.45% of the whole basin. Meanwhile, regions with moderate to high vegetation coverage decreased by 39,148 km<sup>2</sup>, accounting for 24.16% of the PYLB.

Table 4. NDVI characteristics in the PYLB and its change from 2000 to 2020.

Year	2000		2020		2000–2020	
	Area km <sup>2</sup>	Proportion %	Area km <sup>2</sup>	Proportion %	Area Change km <sup>2</sup>	Proportion %
[0–0.2)	1668	1.03	648	0.40	−1020	−0.63
[0.2–0.4)	1419	0.88	2045	1.26	626	0.38
[0.4–0.6)	7597	4.69	5889	3.63	−1708	−1.06
[0.6–0.8)	87,334	53.89	48,186	29.73	−39,148	−24.16
[0.8–1.0]	64,040	39.52	105,289	64.97	41,249	25.45

The vegetation NDVI experienced a significant increasing trend at a rate of 0.0026 from 2000 to 2020 (Figure 5a). As Figure 5b showed, the regions where vegetation experienced significant restoration and slight restoration occupied approximately 58.99% and 29.28% of the basin respectively. The regions where vegetation experienced significant degradation and slight degradation mainly occurred in the urban area and only accounted for 2.84% and 8.66% of the PYLB. There was 0.23% of the basin where vegetation NDVI remained stable.



**Figure 5.** Change trends of vegetation NDVI in the PYLB (a) inter-annual change of the NDVI from 2000 to 2020; (b) the overall change trend of NDVI.

### 3.2. Quantitative Attribution Analysis of the Vegetation Changes

#### 3.2.1. Influence of Natural and Anthropogenic Factors

The factor detector was employed to evaluate the effect of a single factor on vegetation NDVI. The  $q$  value can reflect the explanatory power of the specific factor to vegetation NDVI. The  $q$  value of the selected nine factors in 2020 was in the order of land-use type > slope > elevation > soil type > population density > mean annual temperature > mean annual precipitation > distance to main roads > aspect (Figure 6). The  $q$  value of land-use type was the largest (0.335), which indicated that land-use type can explain more than 30% of the change in NDVI. Thus the land-use type was the dominant factor of vegetation NDVI change. The  $q$  value of slope, elevation, and soil type was 0.283, 0.247, and 0.231 respectively. This indicated that these three factors could explain more than 20% of the change in NDVI, which were also important factors that affected the change in vegetation NDVI. The  $q$  value of the population density and mean annual temperature were 0.184 and 0.146 respectively, which influences on the vegetation could not be neglected. The  $q$  value of mean annual precipitation, distance to main roads, and aspect were all less than 0.1, which meant that these three factors have little influence on vegetation NDVI.

#### 3.2.2. Interaction Effects between Factors

The interactive effects between two driving factors on the NDVI were identified based on the interaction detector. The  $q$  values of the interaction of factors on NDVI were all greater than a single factor (Figure 7), which meant that the interaction of factors all belonged to bi-variable enhanced or nonlinear-enhanced. The  $q$  value of the interaction between land-use type and other factors was greater than that of most other interactions, implying that the land-use type was the dominant factor that influenced vegetation growth. The  $q$  values of the interaction of elevation, slope, soil type with other factors were also relatively high, which indicated that these three factors were important factors influencing vegetation growth. Furthermore, the interaction types of the interaction between factors were explored based on the definition in Table 3. The interaction types of interaction between aspect and soil type, mean annual temperature, land-use type, distance to main roads were nonlinear-enhanced. The interaction types of interactions between soil type and mean annual temperature, soil type and distance to main roads, mean annual temperature, and distance to main roads were nonlinear-enhanced. The interaction types of interactions between other factors were bi-variable enhanced.

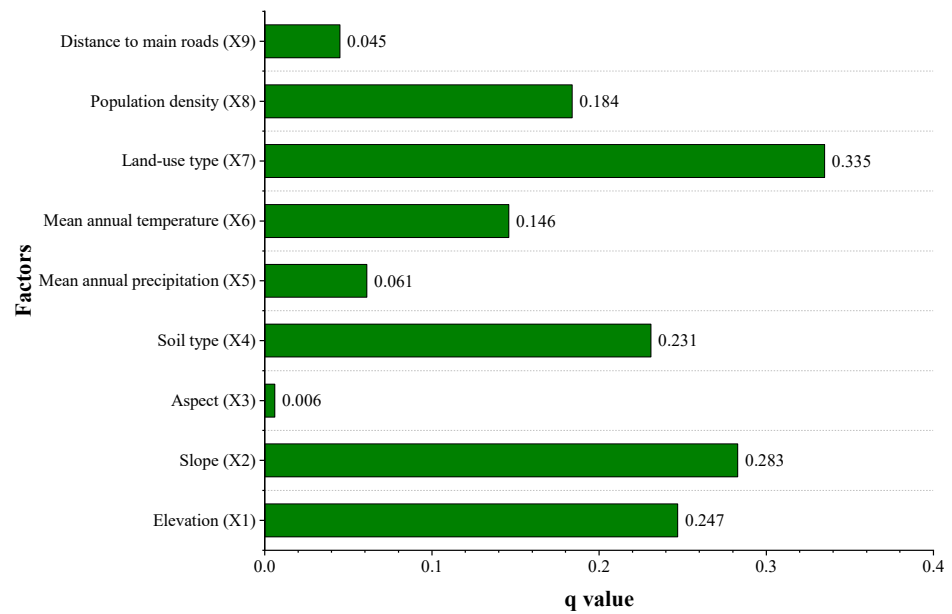


Figure 6. The q values of driving factors in the PYLB.

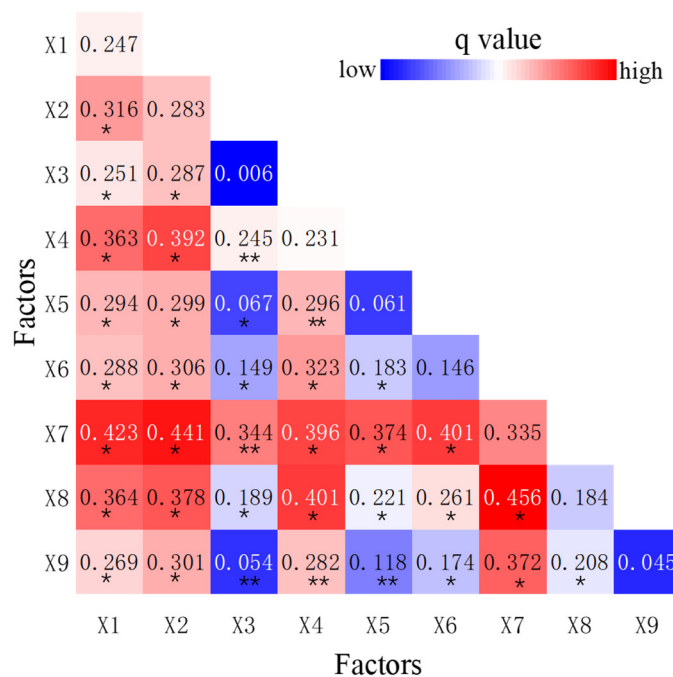


Figure 7. The q values of interaction between factors in the PYLB. Note: “\*” and “\*\*\*” represent the interaction types of bi-variable enhanced and nonlinear-enhanced, respectively.

### 3.2.3. Significant Differences between Factors

The ecological detector was employed to explore whether the influences of two natural or anthropogenic factors on the distribution of vegetation NDVI were significantly different. The results of the ecological detector and statistical significances between natural or anthropogenic were shown in Table 5. There were significant differences between land-use type and all other eight selected factors in the influences of the distribution of vegetation NDVI. This indicated that land-use type was the primary driving factor that determines the distribution of vegetation NDVI in the PYLB. Meanwhile, there were significant differences between the aspect and other factors in terms of the influence of vegetation NDVI, which meant that the aspect exerted little influence on vegetation growth in the PYLB.

Moreover, in terms of the influence of vegetation NDVI, the differences between elevation and slope, mean annual temperature and mean annual precipitation, mean annual temperature and population density, mean annual precipitation and population density were significant. There was no significant difference between other factors in the influence of vegetation NDVI.

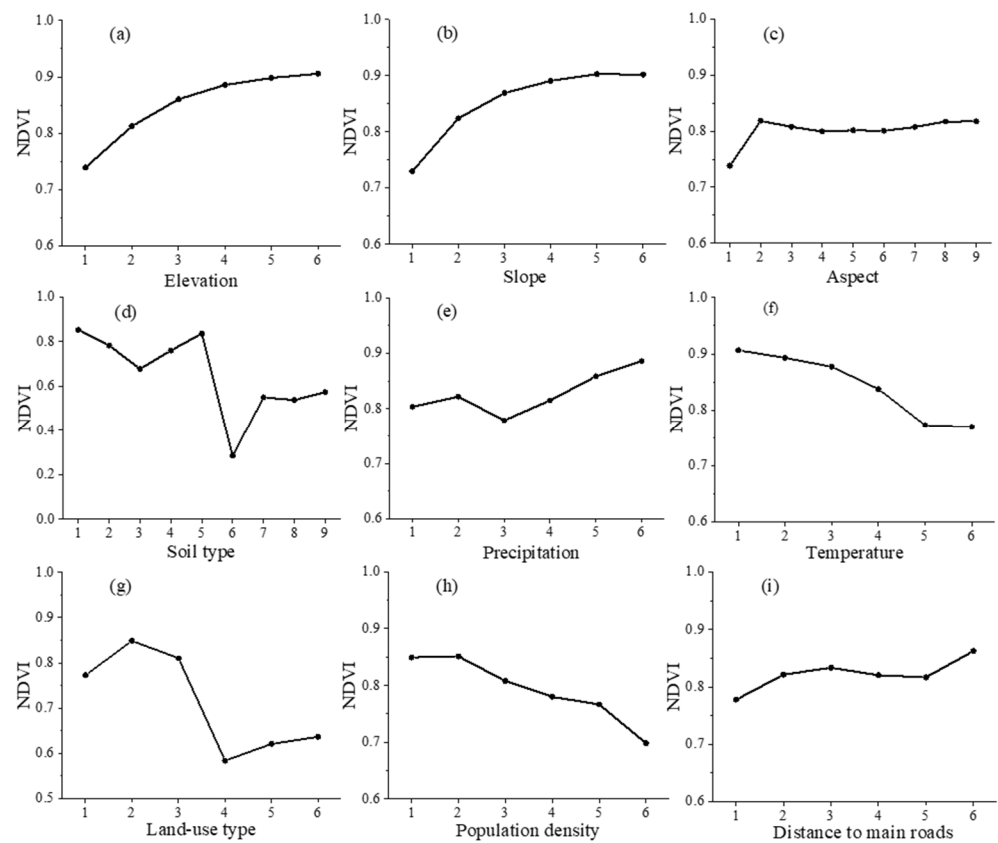
**Table 5.** Significant difference between factors.

Factors	X1	X2	X3	X4	X5	X6	X7	X8	X9
X1									
X2	Y								
X3	N	N							
X4	N	N	Y						
X5	N	N	Y	N					
X6	N	N	Y	N	Y				
X7	Y	Y	Y	Y	Y	Y			
X8	N	N	Y	N	Y	Y	N		
X9	N	N	Y	N	N	N	N	N	

Note: Y means that the influences of two factors on the vegetation NDVI were significantly different at 95% confidence level and N means not.

### 3.2.4. Optimal Types or Ranges of Factors for Vegetation Growth

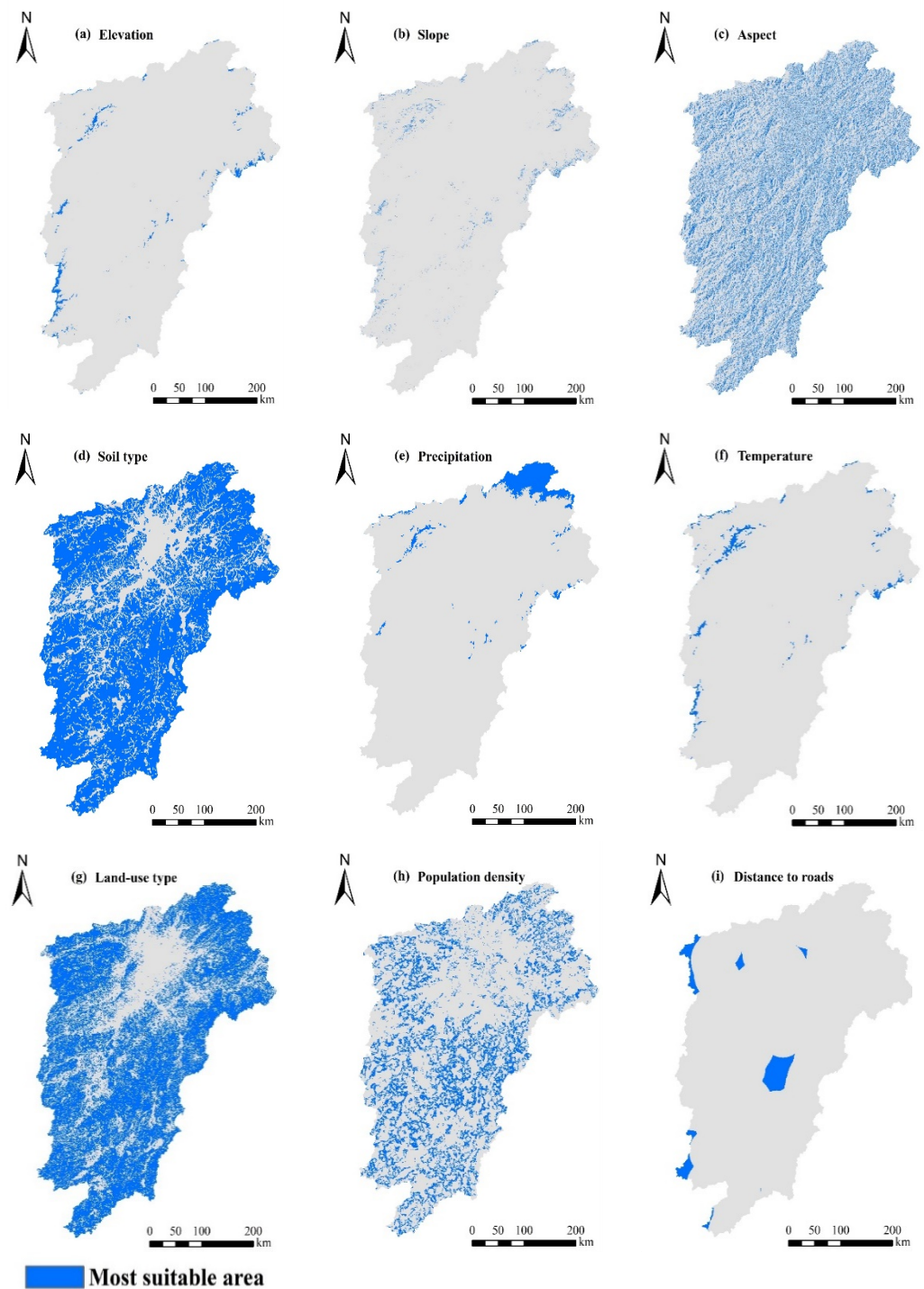
The risk detector was employed to identify whether the mean value of NDVI between two subzones of a driving factor was significantly different and determine the suitable range or type of each driving factor. The response of mean NDVI value to driving factors was shown in Figure 8. The mean value of NDVI changed in different grades of all factors in a non-linear way. In specific, as the elevation increased, the mean NDVI showed an upward trend and reached a maximum value of 0.906 at the regions with an elevation above 984 m. The response of mean NDVI to slope showed similar characteristics as that to elevation, while the NDVI decreased slightly when the slope increased to level 6 (35–46 degrees), indicating that the steep slope was not conducive to vegetation growth. The mean value of NDVI in the gentle slope was much smaller than that in other slopes. In areas with other slopes, it fluctuates slightly. The vegetation NDVI varied greatly in different soil types, reaching its maximum value of 0.837 in the Leached and ferralsol soil indicating that these two types of soil were suitable for vegetation growth. The vegetation NDVI also varied greatly in different land-use type and the maximum and minimum value was observed in forestland and water body respectively. When precipitation was less than 1979.71mm, the response of mean NDVI to the mean annual precipitation of different levels first increased and then decreased. Once the precipitation exceeded that value, the mean NDVI increased with the increase of precipitation and finally reached the maximum value of 0.886. In contrast, the NDVI decreased with the increase in temperature. The NDVI reached its peak value of 0.906 in regions with temperatures ranging from 9.23 to 14.47 °C. The mean NDVI decreased with the increase of population density. When the population density exceeded 400 person/km<sup>2</sup>, the NDVI decreased sharply, which indicated that intensive human disturbance exerted a great adverse effect on vegetation growth. The NDVI reached its peak value of 0.851 in regions with a population density of 50–100 person/km<sup>2</sup>. The NDVI was the lowest in areas less than 5 km away from the roads. When the distance to main roads was larger than 40km, the NDVI reached its maximum value of 0.862. We assumed that the higher the mean value of NDVI, the more suitable the ranges or types of the factor were for vegetation growth. Based on the analysis above, we summarized the ranges or types of factors suitable for vegetation growth as Table 6 based on a *t*-test ( $p < 0.05$ ). This can be helpful for vegetation restoration in the basin in the future. In addition, the spatial distribution of the most suitable range/type for vegetation growth of each factor in the PYLB can be found in Figure 9.



**Figure 8.** NDVI changes with different grades for all factors in the PYLB.

**Table 6.** The factor range/type that suitable for vegetation growth.

Factors	Unit	Appropriate Range/Type	Mean Value of NDVI
Elevation	m	984–2086	0.906
Slope	degree	25–35	0.903
Aspect	categorical	North; West; Northwest	0.818
Soil type	categorical	Leached; Ferralsol	0.837
Mean annual temperature	°C	9.23–14.47	0.906
Mean annual precipitation	mm	2312.02–2982.56	0.886
Land-use type	categorical	Forest	0.849
Population density	people/km <sup>2</sup>	50–100	0.851
Distance to main roads	km	40–67	0.862



**Figure 9.** Spatial distribution of the most suitable area for vegetation growth of each factor in the PYLB.

### 3.3. Effect of Land Use Conversion on Vegetation

Based on the results of the quantitative attribution analysis above, the land use type was found to exert the greatest influence on vegetation change. Thus, we further analyzed the influence of land-use conversions on vegetation change (Table 7). Except for conversion to construction land, most types of land use conversion induced an increase in NDVI in the PYLB. The conversion from cropland to forest, grassland, and water area resulted in an increase of NDVI by 0.053, 0.061, and 0.038, respectively, which accounted for 9.49%, 0.92%, and 1.00% of the whole basin respectively. There were 9.57%, 2.10%, and 0.63%

area of the basin converted from forest to cropland, grassland, and water area, which induced an increase of NDVI by 0.057, 0.061, and 0.070 respectively. The conversion from grassland to cropland, forest, and water area resulted in an increase of NDVI by 0.063, 0.065, and 0.075, respectively, which accounted for 1.00%, 1.96%, and 0.10% of the whole basin respectively. All the conversions from other land-use types to construction land caused a decrease in NDVI. The conversions from other land-use types to unused land counter-intuitively increased NDVI. This may be because the area of these conversions was too small and there was a high error in detecting such conversions.

**Table 7.** NDVI change in different land-use conversion types from 2000 to 2020.

2000\2020	Cropland	Forest	Grassland	Water Area	Construction Land	Unused Land
Cropland	0.031(13.80)	0.053(9.49)	0.061(0.92)	0.038(1.00)	−0.058(1.65)	0.028(<<0.01)
Forest	0.057(9.57)	0.059(49.45)	0.061(2.10)	0.070(0.63)	−0.044(0.84)	0.052(<<0.01)
Grassland	0.063(1.00)	0.065(1.96)	0.073(1.28)	0.075(0.10)	−0.010(0.10)	0.055(<<0.01)
Water area	0.038(1.00)	0.078(0.57)	0.085(0.10)	0.123(2.66)	−0.019(0.16)	\
Construction land	0.012(0.83)	0.031(0.29)	0.029(0.05)	−0.003(0.09)	−0.043(0.35)	\
Unused land	0.083(<<0.01)	0.071(0.01)	\	\	−0.185(<<0.01)	0.169(<<0.01)

Note: the number in parentheses respects the proportion of the specific land-use conversion accounted for the area of the basin(%). “\” means that this land-use conversion type did not happen from 2000 to 2020. “<<” means much less than a certain value.

## 4. Discussion

### 4.1. Characteristics of Vegetation Change in the PYLB

Vegetation change can directly reflect the status of the local environment. In recent decades, vegetation has exhibited a greening trend in most areas of China, such as south-western China [33], the Loess Plateau [56], and the Qinghai-Tibet Plateau [57]. In this study, vegetation NDVI increased in most regions of the PYLB from 2000 to 2020. In general, vegetation NDVI has undergone a fluctuating upward trend at a rate of 0.0026 (Figure 5). The main reason for this finding was that a large proportion of the basin with moderate to high vegetation coverage has converted to high vegetation coverage in the past 21 years (Table 4). These results were in agreement with the previous research in the middle reaches of the Yangtze River. For instance, Chen, et al. [39] indicated that the NDVI in the Hanjiang river basin has increased significantly, which was mainly attributed to the transition from the mid-high area of NDVI to the high NDVI area. Fan, et al. [21] reported that the vegetation NDVI exhibited an increasing trend in 94.9% of the Poyang Lake basin during 2001–2015. The sudden decreases in vegetation NDVI in specific years were mainly caused by extreme weather events. For example, severe droughts occurred in the PYLB in 2000 and 2003, which caused a decrease in NDVI (Figure 5) [58]. The decline in NDVI in 2008 and 2016 should be attributed to severe snowstorm disasters and extreme precipitation events in southern China, respectively [59,60].

The distribution of vegetation NDVI showed obvious spatial heterogeneity in the PYLB. The regions with relatively lower NDVI were mainly distributed in areas with low altitude and flat terrain. The main land-use types in these regions were cropland and construction land, which were characteristic of high human disturbance. Moreover, the result of trend analysis indicated that vegetation degradation was mainly distributed in the urban areas and their surroundings, which might be ascribed to the rapid urbanization, timber production, and land reclamation in the basin in recent decades [21,46]. The expansion of urban and cropland will compress the space of vegetation growth, thus leading to vegetation degradation.

### 4.2. Influences of Driving Factors on Vegetation Change

Vegetation change is a complicated process affected by multiple natural and anthropogenic factors. Quantifying the influences of natural and anthropogenic factors on vegetation change and determining the dominant factor can provide valuable references for decision-makers. Previous studies indicated that the dominant factors of vegetation

change varied from different regions [16,20,39,61]. In this study, the results indicated that both natural and anthropogenic factors exerted great influence on vegetation changes. In general, the vegetation change was highly ( $q$  value  $> 0.2$ , Figure 6) associated with four driving factors (land use type, slope, elevation, and soil type), with land-use type having the greatest contribution.

#### 4.2.1. Influences of Anthropogenic Factors on Vegetation Change

As the most direct reflection of human activities, land use type could dramatically influence regional vegetation growth [27]. In this study, the land use type can explain 33.5% of vegetation change in the basin, which should be considered the dominant driving factor of vegetation change. Most types of land use conversions resulted in an increase in NDVI during the study period (Table 7). For instance, the conversions from cropland to forests and grasslands induced NDVI increased by 0.053 and 0.061, respectively. This should be attributed to the “Grain to Green program” launched in the PYLB in 2002, which object was to convert cropland in hilly areas into forests and grasslands [46]. Meanwhile, many other ecological restoration and afforestation projects such as the “Mountain-River-Lake” project planting trees in the sparse forestland have been conducted in this basin to improve the forest ecosystems in the past decades, which induced an increase of 0.059 in the NDVI of unchanged forest land. The conversions from unused land to croplands and forest, from grassland to cropland and forest have also induced an increase in NDVI, which indicated that reasonable reclamation and afforestation in unused land and low coverage grassland were beneficial to vegetation restoration. This can be approved by the study of Zhu et al. [8]. The NDVI in unchanged cropland increased 0.031, which might be ascribed to the development of modern agriculture technology. However, rapid urbanization could dramatically change the land use and cover and compress the space of vegetation growth, consequently inducing a reduction of vegetation NDVI [29]. In this study, the conversions from other land-use types to construction land all resulted in a decrease in NDVI. This result was in line with previous researches in the middle reaches of the Yangtze River basin [21,39].

In addition to land-use type, in this study, the population density and distance to main roads were also selected to reflect the effect of human activities on vegetation growth. Previous studies indicated that population density is closely related to vegetation cover and high population density is not conducive to vegetation growth [11,18]. In this study, population density could explain 18.4% of vegetation change. The PYLB experienced rapid urbanization and a growing population in recent decades, which exerted a negative influence on vegetation growth [21]. In this study, the highest vegetation NDVI was observed in low population density (50–100 people/km<sup>2</sup>), which was in agreement with previous studies [18,20]. In contrast, the distance to main roads exerted little influence on vegetation change, with a low  $q$  value of 0.045. This was in agreement with Liu, et al. [16].

#### 4.2.2. Influences of Natural Factors on Vegetation Change

The slope was the most important natural factor affecting vegetation change, with a contribution of 28.3%. The change of slope can indirectly affect hydrothermal conditions, soil fertility, and the intensity of human activities, thereby affecting vegetation growth. Previous studies indicated that the slope has an important impact on vegetation growth [18,39]. In this study, vegetation NDVI increased with the increase of slope, while decreased slightly when the slope exceeded 35 degrees. The PYLB is a rapidly developing region, which is characterized by intensive human interference. A certain increase in slope can effectively limit human interference and benefit the growth of vegetation. However, extremely steep slopes are characterized by poor water and fertilizer retention capacity, which is not conducive to vegetation growth. Moreover, the PYLB is located in the subtropical humid region, and sufficient precipitation will cause serious soil erosion on steep slopes, which is not conducive to vegetation growth.

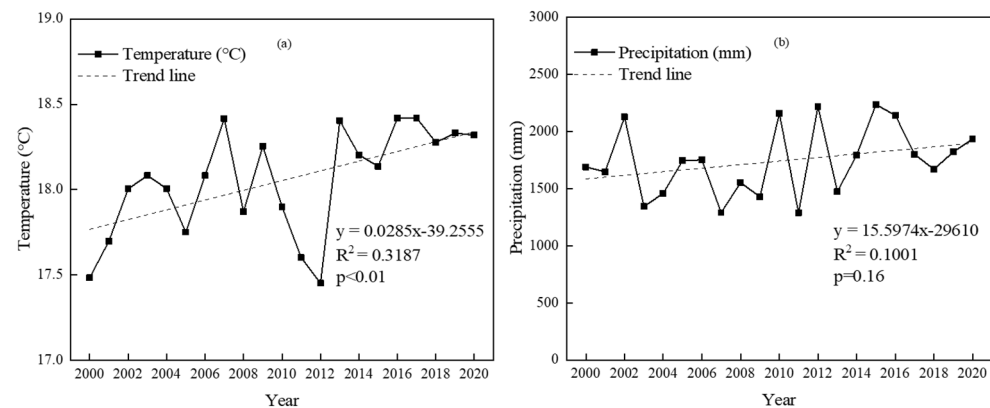


Elevation can explain approximately 24.7% of the vegetation change in the PYLB. Previous researches indicated that there is a threshold for vegetation growth to elevation. For instance, Huo and Sun [20] found a decrease in vegetation cover when the elevation reached more than 3800 m in the Yunnan Plateau. Liu, et al. [57] indicated that the NDVI reached its maximum at 3500 m and then dropped sharply with the increase of elevation in the Tibetan Plateau. The elevation could affect regional hydrothermal conditions and soil nutrition, thereby exerting influence on vegetation growth. High elevation is characterized by low temperature, which will decrease the rate of photosynthesis and soil nutrient release, consequently limiting vegetation growth [20]. However, in this study, NDVI has been increasing with increasing altitude. The reason for this difference should be that elevation of the PYLB is not that high and the negative effect of the change in hydrothermal conditions caused by the elevation increase is smaller than the positive effect of the reduction of human interference caused by it, which will promote vegetation growth. In terms of terrain factors, the influence of aspect was much smaller than that of slope and elevation, which was consistent with previous studies [18,39]. The NDVI in the gentle slope was significantly lower than in other aspects. This is because the gentle slopes of the PYLB mainly occurred in the Poyang Lake area with little vegetation.

Soil type also played a crucial role in vegetation growth, which could explain 23.1% of vegetation change. Different soil types have different characteristics of soil nutrient, structure, and soil moisture content, which could dramatically affect the distribution of vegetation [11,18,20]. Previous research indicated that soil moisture was the limiting factor of vegetation growth in arid regions. For instance, Wang et al. [56] found that the spatial variation in vegetation cover exhibited a positive correlation with the spatial variation in soil moisture content in the Loess Plateau. Li et al. [62] indicated that water availability was the driver of NDVI trend shifts in central Asia. In contrast, soil moisture is not the limiting factor of vegetation growth in humid regions due to sufficient precipitation. In this study, the mean value of vegetation NDVI varied apparently in different soil types in the PYLB. The highest vegetation NDVI was found in leached soil and ferralsol soil, which indicated that these two soil types were most suitable for vegetation growth. This should be ascribed to different soil nutrient characteristics among soil types. For example, the ferralsol soil characterized by fast organic matter decomposition is the most widely distributed soil type in the PYLB, which is very conducive to vegetation growth (Figure 3d). Coupled with suitable hydrothermal conditions, the vegetation type on the ferralsol soil is usually forest with a high NDVI value. It is noteworthy that due to the rapid decomposition of organic matter, once the vegetation is destroyed, severe vegetation degradation and soil erosion will occur on the ferralsol soil. Therefore, vegetation protection and restoration in the PYLB should attach enough attention. In addition, the influence of soil on vegetation distribution can not be simply determined due to their implicated mutual transformation [61].

Climate change is a crucial driving force of vegetation change. Temperature and precipitation are considered the most important climatic factors that affect vegetation distribution and change [7,9,11]. The temperature has been proved to be important in affecting vegetation change in high elevation regions such as the Qinghai-Tibetan Plateau [16] and Sichuan [17], while the influence of precipitation is significant in arid and semiarid regions [8]. In this study, the temperature showed a significant increasing trend ( $p < 0.01$ ), while the increase in precipitation was not significant in the PYLB during the study period (Figure 10). This indicated that the climate become wetter and warmer in the past two decades in the PYLB, which is conducive to vegetation growth. In this study, compared with other factors, both the  $q$  value of temperature and precipitation were relatively not high. Temperature and precipitation were not the growth limiting factors in subtropical humid regions like the PYLB, thus temperature and precipitation exerted little influence on the vegetation change. This was consistent with the study of Chen et al. [39]. Moreover, the  $q$  value of temperature was more than twice of precipitation (0.146 vs. 0.061), which meant that the temperature exerted greater influence on vegetation change than precipitation in the PYLB. The reason should be that vegetation has adapted well to temperature and the

spatial pattern of temperature is relatively stable, while the spatial pattern of precipitation varies greatly in different years.



**Figure 10.** Trends in temperature and precipitation in the PYLB from 2000 to 2020.

#### 4.3. Interactive Effects of Natural and Anthropogenic Factors on Vegetation Change

The vegetation changes are not influenced by a single factor, but the synthetic interaction effect of different factors. Previous studies indicated that the interactive influence of two factors was always stronger than that of a single one [8,17]. In this study, the interactive effect of two factors mainly showed mutual and nonlinear enhancement. Although the effects of aspect, precipitation, and distance to main roads on vegetation change were relatively weak, they can be enhanced when interacting with other factors. Specifically, this trend can be found, for example, in the interactions of precipitation and elevation ( $q(X2 \cap X5) = 0.299$ ,  $q(X5) = 0.061$ ), aspect and soil type ( $q(X3 \cap X4) = 0.245$ ,  $q(X3) = 0.006$ ), distance to roads and land use type ( $q(X9 \cap X7) = 0.372$ ,  $q(X9) = 0.045$ ). This was consistent with previous studies [16,18,61]. In addition, the interaction of land use type and population density exerted the greatest influence on vegetation change, which can explain 45.6% of vegetation change, indicating that human activities dominated the vegetation change in the PYLB from 2000 to 2020.

#### 4.4. Implication and Limitations

Vegetation change is a complex process affected by the complex interaction of natural and anthropogenic factors. This study adopted the Geodetector model to quantify the contribution of different driving factors and their interactions to vegetation change in subtropical regions. Previous studies on the driving mechanism of vegetation change based on Geodetector were mainly conducted in regions with low intensity of human activities and concluded that natural factors were the dominant factor affecting vegetation change [16,39,61]. This study also indicated that natural factors like elevation, slope, and soil type exerted an important influence on vegetation change. However, the difference is that we found that the anthropogenic factors were the dominant driving force of vegetation change in the PYLB. The reason is that the PYLB is a rapidly developing region with intensive human activities. In recent decades, this basin has experienced rapid urbanization and implemented multiple ecological restoration programs like the “Grain to Green program”, which have dramatically changed the landscape, thereby directly influencing vegetation change [46]. There remain certain limitations in this study. For example, the potential factors affecting vegetation growth selected in this study are not comprehensive. Some other natural and anthropogenic factors (e.g., solar radiation, relative humidity, vegetation type, geomorphic type, GDP) should be taken into consideration in future research [16,18,20,39]. Despite these limitations, this study effectively quantified the relative contribution of main driving factors and their interactions to vegetation change. In addition, we have also determined the most suitable range or type of potential driving factors for vegetation growth in the PYLB, which can be helpful for decision-makers to optimize the implementation

of ecological projects. The results of this study can improve understanding of the driving mechanisms of vegetation change in subtropical humid regions and provide a valuable reference for the ecological restoration in the PYLB.

## 5. Conclusions

This study used NDVI as an indicator and adopted the Geodetector model to quantify the influences of natural and anthropogenic factors and their interaction on NDVI change in the PYLB from 2000 to 2020. The main conclusions are summarized in the following points. (1) Most regions of the PYLB were experiencing vegetation restoration and the NDVI showed an increasing trend with fluctuation at a rate of 0.0026 during the study period. (2) Land-use types made the greatest contribution to vegetation change, followed by slope, elevation, and soil types. (3) Except for conversions to construction land, most types of land use conversion induced an increase in NDVI in the PYLB from 2000 to 2020. (4) The influence of one factor on vegetation NDVI was always enhanced when interacting with another. The interaction effect of land-use types and population density was the largest, which could explain 45.6% of the vegetation NDVI change, indicating that human activities dominated vegetation change in the PYLB. (5) Using the risk detector, we determined the ranges or types of factors suitable for vegetation growth in the PYLB, which can help optimize subsequent vegetation restoration in the basin in the future.

**Author Contributions:** All authors contributed to the design of this research and the writing of the manuscript. Y.W. analyzed the data and wrote the manuscript. Z.Z. and X.C. reviewed and offered suggestions for further improvements to the manuscript. All authors have read and agreed to the published version of the manuscript.

**Funding:** This research was funded by The National Key Research and Development Project of China (Grant no. 2019YFC0409004) and the National Natural Science Foundation of China (Grant No.41971025).

**Institutional Review Board Statement:** Not applicable.

**Informed Consent Statement:** Not applicable.

**Data Availability Statement:** The data presented in this study are available on request from the corresponding author. The data are not publicly available due to privacy.

**Acknowledgments:** We would like to thank the National Climate Centre in Beijing for providing valuable climate datasets. In addition, We sincerely thank the editor and anonymous reviewers for their valuable comments and suggestions to improve the quality of this paper.

**Conflicts of Interest:** The authors declare no conflict of interest.

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