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Spatial Pattern of Changing Vegetation Dynamics and Its Driving Factors across the Yangtze River Basin in Chongqing: A Geodetector-Based Study

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Abstract: Revealing the spatial dynamics of vegetation change in Chongqing and their driving mechanisms is of major value to regional ecological management and conservation. Using several data sets, including the SPOT Normalized Difference Vegetation Index (NDVI), meteorological, soil, digital elevation model (DEM), human population density and others, combined with trend analysis, stability analysis, and geographic detectors, we studied the pattern of temporal and spatial variation in the NDVI and its stability across Chongqing from 2000 to 2019, and quantitatively analyzed the relative contribution of 18 drivers (natural or human variables) that could influence vegetation dynamics. Over the 20-year period, we found that Chongqing region's NDVI had an annual average value of 0.78, and is greater than 0.7 for 93.52% of its total area. Overall, the NDVI increased at a rate of 0.05/10 year, with 81.67% of the areas undergoing significant expansion, primarily in the metropolitan areas of Chongqing's Three Gorges Reservoir Area (TGR) and Wuling Mountain Area (WMA). The main factors influencing vegetation change were human activities, climate, and topography, for which the most influential variables respectively were night light brightness (NLB, 51.9%), annual average air temperature (TEM, 47%), and elevation (ELE, 44.4%). Furthermore, we found that interactions between differing types of factors were stronger than those arising between similar ones; of all pairwise interaction types tested, 92.9% of them were characterized by two-factor enhancement. The three most powerful interactions detected were those for NLB ∩ TEM (62.7%), NLB ∩ annual average atmospheric pressure (PRS, 62.7%), and NLB ∩ ELE (61.9%). Further, we identified the most appropriate kind or range of key elements shaping vegetation development and dynamics. Altogether, our findings can serve as a timely scientific foundation for developing a vegetative resource management strategy for the Yangtze River basin that duly takes into account local climate, terrain, and human activity.

Keywords: normalized difference vegetation index (NDVI); spatial evolution; multi-factor interaction; geographic detector

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1. Introduction

Vegetation is an important component of terrestrial ecosystems and serves as a link between the atmosphere, water, and soil [1], thus playing a pivotal role in soil conservation, climate regulation, hydrological processes, the carbon cycle, and ecosystem functioning and stability [2,3]. The health of a local ecological environment, such as its water quality, thermal energy, and soil fertility, can also be gauged by its vegetation [4]. Hence, vegetation is often used not only as an indicator of an ecosystem's sensitivity to external disturbances, such as climate change and human activities [5], but also as a comprehensive indicator for characterizing the response and adaptation of a terrestrial ecosystem to environmental change. Accordingly, understanding vegetation's spatio-temporal evolution and the involved driving mechanisms is critical for the regional development of effective vegetation restoration measures and ecological protection policies [6].

Monitoring vegetation dynamics has been a major focus of global change research in recent decades [7]. Because of their unique advantages, namely their large spatial scale, long time series, and short interval period, remote sensing images have become the primary data source for monitoring vegetation change at different scales, especially at multiple spatio-temporal scales [8]. For example, Schultz et al. [9] used a long-time series of Landsat-derived remote sensing imagery to monitor deforestation throughout the tropics. With the continued maturation and development of hyperspectral and thermal infrared remote sensing technologies, the bands of their images are becoming more abundant, making it feasible to use them to study changing spatio-temporal dynamics of terrestrial vegetation. To that end, researchers in China and abroad have proposed more than 100 plant cover indexes, such as the ratio vegetation index (RVI), difference vegetation index (DVI), normalized difference vegetation index (NDVI), enhanced vegetation index (EVI), soil adjusted vegetation index (SAVI), and so forth [10,11], greatly improving the efficiency and accuracy of extracting vegetation information. Currently, of those, the NDVI is recognized as the best indicator of regional vegetation and ecological environment change because its value can convey real information about vegetation's growth status and biomass, among other things; hence, it is widely used in the study of vegetation dynamics [12–14].

The dynamics of vegetation and the involved mechanisms shaping it have drawn much attention in the context of rapid global change [15,16]. Many studies have shown that vegetation dynamics are closely related to a broad suite of natural factors, including climate, terrain, soil, and vegetation types [17,18]. How vegetation responds to climate change is a very complex process, and climatic factors such as precipitation, temperature, and evapotranspiration can jointly affect vegetation dynamics. For instance, Na et al. [17] examined the impact of shifts in extreme air temperature and extreme precipitation indexes on the long-term dynamics of vegetation in inner Mongolia, finding that climate change may explain 68% of the variation in that vegetation's development. The effect of evapotranspiration on vegetation change should not be overlooked either, according to Shuai et al. [18], given the rapid acceleration of surface change. By analyzing the suitable growth conditions of vegetation in the Weihe River Basin, Zhang et al. [19] showed that NDVI is strongly correlated with air temperature, precipitation, evaporation, and soil moisture, with correlation coefficients as high as 0.89, 0.78, 0.71, and 0.65, respectively. The Yangtze River Basin is the largest basin in Asia, and its vegetation cover status and dynamics are fundamental to maintaining the ecological balance of China and its neighboring countries, and perhaps even that of the whole world.

In recent years, great progress has been made in the study of the changing dynamics of NDVI and its influencing factors in the Yangtze River Basin. According to some studies, this basin's NDVI featured an overall upward trend during the years spanning 1982 to 2015, increasing in extent mainly in its middle while decreasing chiefly in its eastern part [20–22]. Furthermore, Qu et al. [20] found that this NDVI trend was more pronounced after 1994 than before. Temperature is the main climatic factor affecting the growth of vegetation in the Yangtze River Basin, while precipitation has a weak effect on it [21]. Other work has reported evidence for lag effects from altered precipitation and temperature regimes on vegetation growth in the Yangtze River Basin, with more than 50% of this growth (on a regional scale) predominantly affected by climate change. Because studies of the whole Yangtze River Basin or portions of it mostly focused on temperature and precipitation, less is known about the possible influences of other climatic factors, in addition to topographic factors and human activities, on vegetation growth and dynamics there [23,24].

Traditional statistical methods, such as linear regression and residual trend analysis, can be applied to reveal the relationship between the monotonous trend of vegetation change and its drivers, but this inference is limited to linear relations [25,26]. However, we know that vegetation growth is often affected by the joint action of multiple factors, so how natural and human factors interact to change vegetation dynamics is unlikely to be a simple linear relationship [27]. Therefore, determining how to accurately quantify the relative contributions of natural and human factors to regional vegetation change and the driving mechanisms involved remains a challenging task [28,29]. The geographic detector model based on spatial stratification heterogeneity theory, introduced by Wang et al. [30,31], provides a reliable and direct methodology to quantify the respective influence of driving factors as well as their interactions. It has three notable advantages: (i) it does not have to strictly follow the assumptions of traditional statistical methods; (ii) it does detect the interaction of two factors, and (3) it does not require a complex parameter setting process [15,32,33]. For example, Zhu et al. [29] quantified the impacts of natural and human factors on changing vegetation dynamics in the middle reaches of the Heihe River by using geographic exploration methods, which revealed that land use conversion type, average annual precipitation, and soil type had the greatest impact. Li et al. [34] quantitatively analyzed the driving factors of grassland vegetation in inner Mongolia from the perspective of spatial stratification heterogeneity, finding that precipitation, livestock density, wind speed, and humans population density were the dominant factors, with these accounting for more than 15% of variation in the data. As such, the geographic detector approach has been successfully applied to quantify the influence of potential driving factors on vegetation dynamics, making it an effective tool for understanding the mechanisms of vegetation change at different spatial scales.

The Chongqing municipality in China is located in the upper reaches of the Yangtze River and in the central zone of the Three Gorges Reservoir Area. It is the last pass of the ecological barrier in the upper reaches of the Yangtze River, and its ecological location is crucial. Therefore, building an important ecological barrier in the upper reaches of the Yangtze River plays an indispensable role in ensuring the ecological balance and homeland security of the entire Yangtze River basin. In recent years, with the intensification of global climate change and human activities, understanding the spatio-temporal dynamic evolution of vegetation in this region and its driving mechanisms has become imperative for the development of reasonable ecosystem protection measures and management in this region. To achieve this aim, based on a time series of SPOT NDVI data, we used trend analysis, stability analysis, and geographic detector methods to fulfill three objectives: (1) to reveal the spatial characteristics and regularities of NDVI-based vegetation dynamics in Chongqing during the years 2000–2019; (2) to quantify the driving mechanisms of natural factors and human activities and their interactions upon vegetation change; and (3) to explore the appropriate types or ranges of the main influencing factors that promote vegetation growth in Chongqing, so as to provide a reference for the implementation of vegetation restoration projects in the Yangtze River Basin and the formulation of sound ecological environmental protection policies.

2. Materials and Methods

2.1. Study Region

Chongqing is located in the transitional zone between the Qinghai-Tibet Plateau and the plain of the middle/lower reaches of the Yangtze River, where it encompasses an area of 8.24×10^4 km^2 (Figure 1a). Aside from being a significant industrial and commercial center in the southwest, a marine and land transportation hub, and the greatest economic hub in the upper reaches of the Yangtze River, Chongqing also serves as a crucial ecological barrier to protect those areas. Implementation of the "one district and two clusters" coordinated development spatial pattern—the major city metropolitan area (MCA), the Three Gorges Reservoir Area town cluster in northeast Chongqing (TGR), and the Wuling Mountain Area town cluster in southeast Chongqing (WMA)—is being accelerated (Figure 1b). In going from south and north to the middle valley area, the topography gradually flattens out, with elevations spanning 63 to 2624 m. The geography varies greatly and is complex, with low mountains and hills in the northwest and center, and Daba Mountain and Wuling Mountain in the southeast (Figure 1c). The Yangtze River, Jialing River, Wujiang River, Fujiang River, Qijiang River, Daning River, and other major rivers flow through this region, which is endowed with abundant surface water resources. Here, a subtropical humid monsoon climate prevails, with annual averages ranging from 4.7–19.7 °C for air temperature, 7.3–21.7 °C for ground temperature, 989–1682 mm for precipitation, 640–1015 mm for evapotranspiration, 79–1646 h for sunshine duration, and 0.8%–84.5% for relative humidity. Leaching soil, primary soil, man-made soil, and iron-bauxite are the main soil types. There are many different types of vegetation, and the vegetation that exists in this region is mostly cultivated crops, shrubs, and other plants (Figure A1).

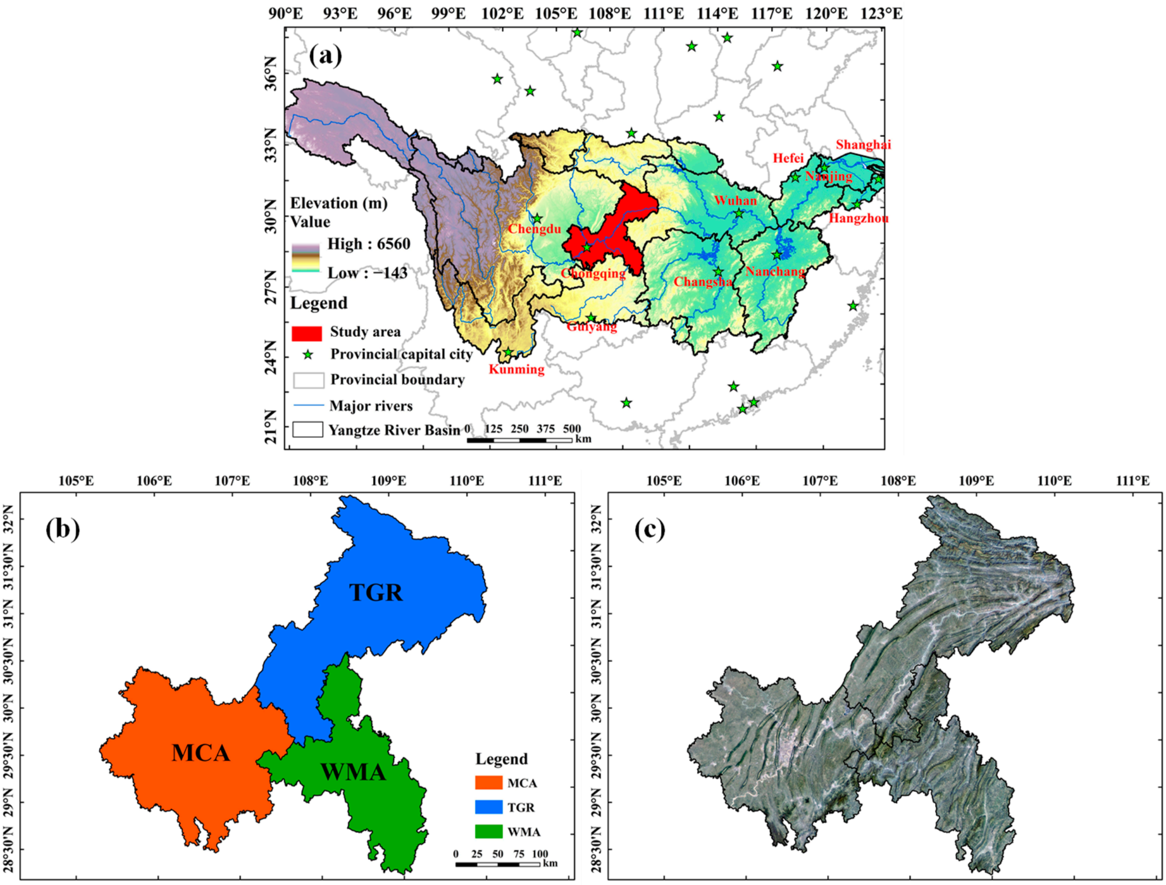

Figure 1. Overview of the study region. (**a**) Its location in the Yangtze River Basin in China; (**b**) the "one district and two clusters" coordinated development spatial pattern; (**c**) original remote sensing image. Notes: MCA, the major city metropolitan area; TGR, Three Gorges Reservoir Area town cluster in northeast Chongqing; and WMA, the Wuling Mountain Area town cluster in southeast Chongqing.

2.2. Data Source and Preprocessing

2.2.1. NDVI Data

The growing status of vegetation on the land surface can be accurately expressed by a vegetation index. In this study, we chose the SPOT NDVI dataset based on the following considerations. (1) Currently, the monitoring of changing vegetation dynamics at various scales has made extensive use of the NDVI time series data derived from SPOT satellite remote sensing imagery [12,35]. (2) The SPOT NDVI dataset with a time span of 2000 to 2019 can be obtained directly from the Resource and Environmental Science Data Center of the Chinese Academy of Sciences (https://www.resdc.cn/, accessed on 18 June 2022) and is free. (3) This data, with a spatial resolution of 1000 m, is consistent with the spatial resolution of mostly other research data (Table 1), and can avoid the influence of data pre-processing processes, such as resampling, on the research results. (4) Since the general quality of this data set is very high based on the maximum value composite (MVC) method, it can accurately reflect the amount and distribution of vegetation in different regions at various geographical and temporal scales; it is now widely used in monitoring regional vegetation change [29,36].

Table 1. The 18 factors considered in this study for their influence on changing vegetation dynamics.

Category	Variable	Time Series	Pixel Resolution	Units	Abbrev.
Climate	Annual average precipitation	2000s/2010s	1000 m	mm	PRE
	Annual average evaporation	2000s/2010s	1000 m	mm	EVP
	Annual average relative humidity	2000s/2010s	1000 m	%	RHU
	Annual average air temperature	2000s/2010s	1000 m	°C	TEM
	Annual average ground temperature	2000s/2010s	1000 m	°C	GST
	Annual sunshine hours	2000s/2010s	1000 m	hour	SSD
	Annual average atmospheric pressure	2000s/2010s	1000 m	hPa	PRS
Soil	Soil type	1995	1000 m	-	SOT
	Soil sand content	2000s	1000 m	%	SSAC
	Soil silt content	2000s	1000 m	%	SSIC
	Soil clay content	2000s	1000 m	%	SCLC
Vegetation	Vegetation type	2000	1000 m	-	VET
Topography	Elevation	2000	250 m	m	ELE
	Slope degree	2000	250 m	°	SLD
Human activity	Land use type	2000/2010/2020	1000 m	-	LUT
	Gross domestic product density	2000/2010/2019	1000 m	10^4 Yuan/km^2	GDP
	Population density	2000/2010/2019	1000 m	persons/km^2	POP
	Night light brightness	2000–2019	1000 m	DN	NLB

2.2.2. Influence Factor Data

Numerous studies have demonstrated that a broad range of factors influence vegetation dynamics [33,37,38]. We concentrated on five components and 18 variables related to climate, soil, vegetation, topography, and human activities (Table 1). The climatic data come from the spatial interpolation data set of the average state of meteorological elements in China [39]. The ANUSPLIN meteorological interpolation software's smoothing spline function was primarily used to obtain the climatic data, which included seven meteorological variables: annual average precipitation (PRE), annual average evaporation (EVP), annual average relative humidity (RHU), annual average air temperature (TEM), annual average ground temperature (GST), annual sunshine hours (SSD), and annual average atmospheric pressure (PRS). Data for soil types was obtained from the 1:1 million Soil Map of the People's Republic of China—created and published by the National Soil Survey Office in 1995—while that for soil sand, silt, and clay content was generated by that soil type map and soil profile information from the second soil survey. Most of the vegetation information came from the "1:1 million Vegetation Atlas of China". The elevation in the terrain data was derived from a 90-m digital elevation model (DEM) and slope data in ArcGIS 10.7 software. Human activities include land use data generated by artificial visual interpretation, this based on American Landsat TM images, and spatial distribution data sets for China's GDP [40] and population [41], which are constantly updated by data producers. All the above data are from the Resource and Environmental Science Data Center of the Chinese Academy of Sciences (https://www.resdc.cn/, accessed on 8 October 2022). Additionally, the National Qinghai-Tibet Plateau Science Data Center (https://data.tpdc.ac.cn, accessed on 19 June 2022) in China provided the long time series data for remote sensing of night light as one indicator of human activity [42].

To meet the input requirements of the geographic detector model, we divided vegetation type into seven categories: coniferous forest, broad-leaved forest, shrub, grass, meadow, cultivated vegetation, and other vegetation. Similarly, we divided land use type into nine categories: cultivated land, woods, shrubs, sparse woodland, other woodland, grassland, water, urban and rural residential land, and unused land. Six categories of soil type data were distinguished: leaching soil, primary soil, hemihydrate soil, artificial soil, iron bauxite, and non-soil type. Additionally, by applying the natural discontinuity approach [43], the remaining 15 continuous variables were classified into 10 groups. Using ArcGIS 10.7, we cast a 2-km fishnet, to extract the NDVI and the effect variables to the point, and then applied the geographic detector's calculation after removing null values.

2.3. Methods

2.3.1. Trend Analysis

To explore the spatial distribution characteristics of the multi-year vegetation NDVI in Chongqing, its yearly average NDVI was calculated from 2000 to 2019. We used linear regression analysis to examine the temporal trend change of NDVI in Chongqing from 2000 to 2019, using pixels as the fundamental unit. Its mathematical equation is:

$$slope = \frac{n\sum_{i=1}^{n} NDVI_i - (\sum_{i=1}^{n} i)(\sum_{i=1}^{n} NDVI_i)}{n\sum_{i=1}^{n} i^2 - (\sum_{i=1}^{n} i)^2} \quad (1)$$

where $slope$ is the magnitude and direction of vegetation change, n is the number of years of studied (n = 20 in this study), i denotes a given year from 2000 onward, and $NDVI_i$ denotes the NDVI value for ith year of a pixel.

2.3.2. Stability Analysis

Each observation's level of variation was measured and evaluated statistically using the coefficient of variation (CV). In this time series, CV can indicate the stability of the NDVI data for Chongqing: stronger stability is inferred by a smaller CV value, and weaker stability by a larger CV value [44]. The CV is calculated this way:

$$CV = \frac{\sqrt{\sum_{i=1}^{n} \left(NDVI_i - \overline{NDVI}\right)^2 / (n-1)}}{\overline{NDVI}} \quad (2)$$

where $NDVI_i$ denotes the NDVI value for ith year of a pixel, and $\overline{NDVI}$ is the overall average value of NDVI for the whole study period (2000–2019). To more easily compare and convey the variation in vegetation inferred from NDVI across Chongqing, we separated the CV values into four grades, corresponding to extremely stable vegetation ($CV \leq 0.1$), general stable vegetation ($0.1 < CV \leq 0.2$), general unstable vegetation ($0.2 < CV \leq 0.3$), and extremely unstable vegetation ($CV > 0.3$).

2.3.3. Geodetector Model

Geographic detector is a relatively new spatial statistical technique developed by Wang Jinfeng and colleagues that was introduced in 2010 [30,31]. It is typically used to investigate the regional variability of vegetation change and its drivers, and to quantify how potential interactions of these factors may affect the response variables [15,37,38]. It is based on four modules: factor detector, interaction detector, risk detector, and ecological detector.

(1) Factor detector

Its purpose is to detect the spatial heterogeneity of a dependent variable, in this case vegetation NDVI, and to explore the degree to which candidate influencing factors (i.e., the 18 variables in Table 1) could explain that, this expressed as:

$$q = 1 - \frac{\sum_{h=1}^{L} N_h \sigma_h^2}{N\sigma^2} \quad (3)$$

where q can reflect the degree of interpretation of vegetation dynamics by detection factors; $h = 1, 2, \ldots, L$ is the strata of the dependent variable (vegetation NDVI) or of each influencing factor investigated; N_h and N are respectively the number of samples units in layer h and for the whole region; and σ_h^2 and σ^2 denote the variance of the layer h and the NDVI value of the whole region, respectively. The q statistic can take a value in the range of 0 to 1; the higher its value, the greater the power of its corresponding influencing factor to explain vegetation change.

(2) Interaction detector

This may be used to analyze whether the interaction of any two factors will increase or decrease their respective explanatory power for vegetation change, or whether the effects of either factor upon NDVI are independent of each other. The following five categories can be used to illustrate how the two factors could interact (Table 2).

Table 2. Interaction types of factors that affect changing vegetation dynamics.

Number	Judgments Based	Type of Interaction
1	$q(X1 \cap X2) < \mathrm{Min}(q(X1), q(X2))$	Non-linear reduction
2	$\mathrm{Min}(q(X1), q(X2)) < q(X1 \cap X2) < \mathrm{Max}(q(X1), q(X2))$	Single-factor non-linear reduction
3	$q(X1 \cap X2) > \mathrm{Max}(q(X1), q(X2))$	Two-factor enhancement
4	$q(X1 \cap X2) = q(X1) + q(X2)$	Independent
5	$q(X1 \cap X2) > q(X1) + q(X2)$	Non-linear enhancement

(3) Ecological detector

This module is primarily used to assess whether there is a statistical difference between the two factors in relation to the spatial distribution of the attribute of interest, here NDVI, which is often tested using the F-ratio statistic:

$$F = \frac{N_{x1}(N_{x2} - 1)SSW_{x1}}{N_{x2}(N_{x1} - 1)SSW_{x2}} \tag{4}$$

where N_{x1} and N_{x2} are the total sample size of each of the two factors; and SSW_{x1} and SSW_{x2} denote the summed intra-layer variance formed by $x1$ and $x2$, respectively. If the null hypothesis of $H_0 : SSW_{x1} = SSW_{x2}$ is rejected at the alpha level of significance, then a significant difference between the two factors is inferred for how they influence the spatial distribution of NDVI.

(4) Risk detector

It is frequently used to determine whether there is a statistically significant difference in the mean value of attributes between the two subregions. To test this, the Student's t-test is typically used.

The Geodetector Software in Excel was used as the geographic probe in this study. It is freely available for download online. For more details about Geodetector modeling, please see http://geodetector.cn/, accessed on 10 June 2022.

3. Results

3.1. NDVI's Interannual Variation

As Figure 2 shows, Chongqing's vegetation tended to increase over time, but some regional differences at various geographical scales were evident. From 2000 to 2019, the NDVI increased strongly, at a rate of 0.05/10 year, reaching its maximum value (0.83) in 2017 and its minimum value (0.71) in 2000. Examining the interannual dynamics, we see that the rate of NDVI increase for 2011–2019 was 1.80, 1.33, and 1.43 times greater than that for the 2000–2010 period in the MCA, WMA, and TGR subregions, respectively. This revealed that vegetation restoration was considerably more effective during 2011 to 2019 than 2000 to 2010. Spatially, the NDVI increased at a faster rate in the WMA (0.07/10 year) and TGR (0.06/10 year) than in the MCA (0.03/10 year).

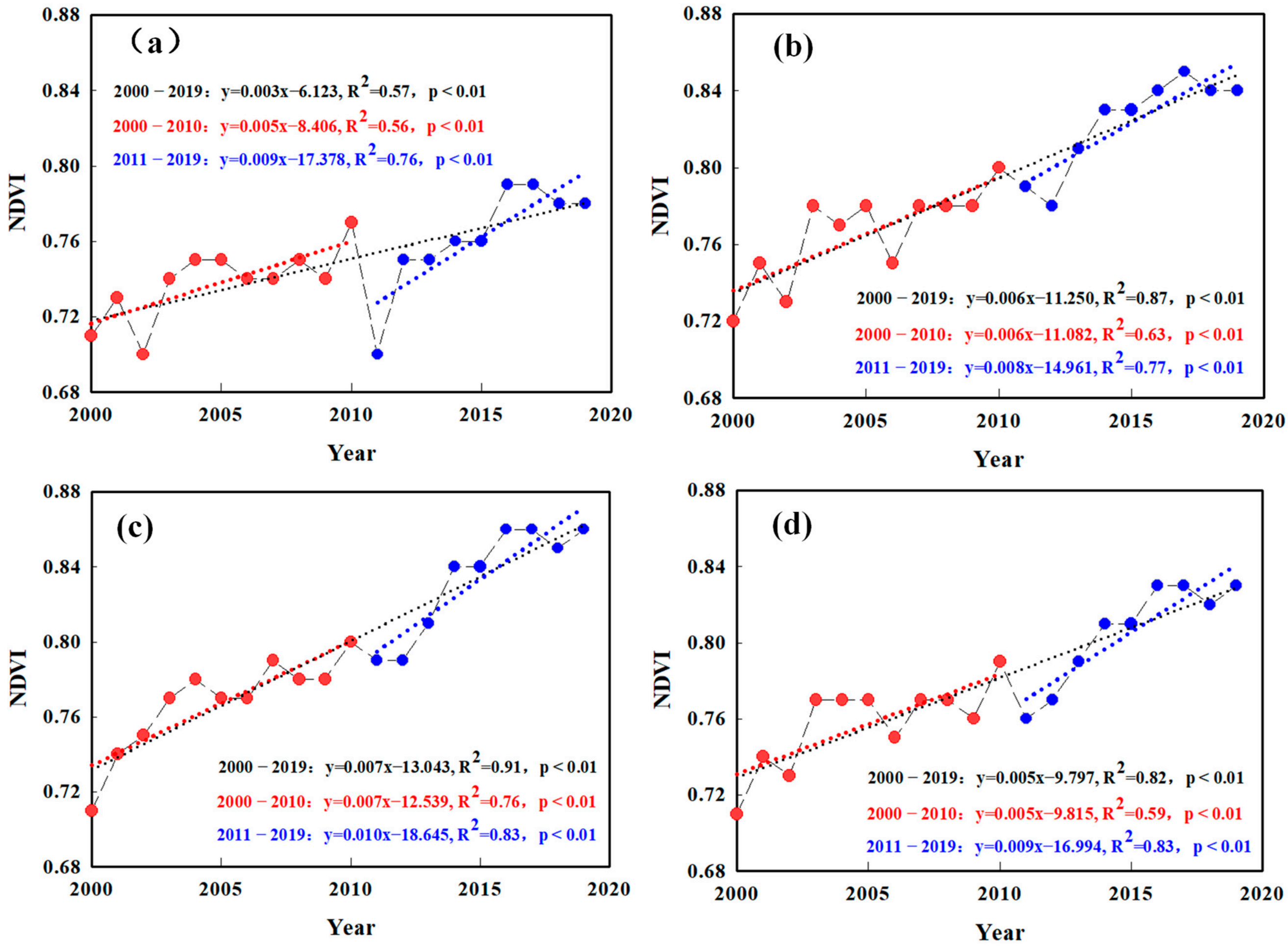

Figure 2. Interannual dynamics of vegetation NDVI in different regions of Chongqing, China, from 2000 to 2019. (**a**) The major city metropolitan area (MCA); (**b**) the Three Gorges Reservoir Area town cluster in northeast Chongqing (TGR); (**c**) the Wuling Mountain Area town cluster in southeast Chongqing (WMA); (**d**) all of Chongqing.

3.2. NDVI's Spatial Distribution

The regional distribution characteristics of NDVI in Chongqing from 2000 to 2019 are depicted in Figure 3 and Table 3. In 2000, 2010, and 2019, the values for NDVI were mainly in the range of 0.6–0.8, >0.7, and >0.7, respectively, with these respectively accounting for 92.21%, 96.91%, and 93.39% of Chongqing's total area. Only 3.35%, 0.63%, and 3.42% of the Chongqing area had NDVI values below 0.6. The percentage of its land area with an NDVI > 0.8 expanded substantially, from 4.45% in 2000 to 75.88% in 2019, a net increase of 71.43%. Chongqing's average NDVI over the entire 20-year period (2000 to 2019) was 0.78, with values primarily distributed between 0.70 and 0.80 that characterized 59.6% of its entire area. The multi-year average of NDVI in the WMA, TGR, and MCA was 0.80, 0.79, and 0.75, respectively.

The regional distribution of trends in the NDVI's change over time in Chongqing is depicted in Figure 4a and Table 4. Those areas distinguished by obvious vegetation restoration (i.e., NDVI rate of increase > 0.07/10 year) together accounted for 28.37% of Chongqing's territory, being mainly distributed in the TGR (42.8%) and WMA (31.05%). Roughly 1.49% of Chongqing's total area consisted of declining NDVI (i.e., a changing slope of less than −0.01/year), this primarily concentrated in the MCA. We found areas with an extremely significant recovery of NDVI as high as 75.19%; these were chiefly concentrated in the WMA and TGR. The parts of Chongqing featuring extremely significant and significant degradation areas, respectively, amounted to just 1.94% and 0.85% of its total area, being mainly concentrated in the MCA (Figure 4b and Table 4). Overall, 52.19% of the study area's vegetation dynamics are in an extremely stable state. Where extremely unstable and general unstable vegetation dynamics did occur, this only affected 1.38% and 3.61% of the total area, principally in the MCA and along either side of the Yangtze River (Figure 4c and Table 4).

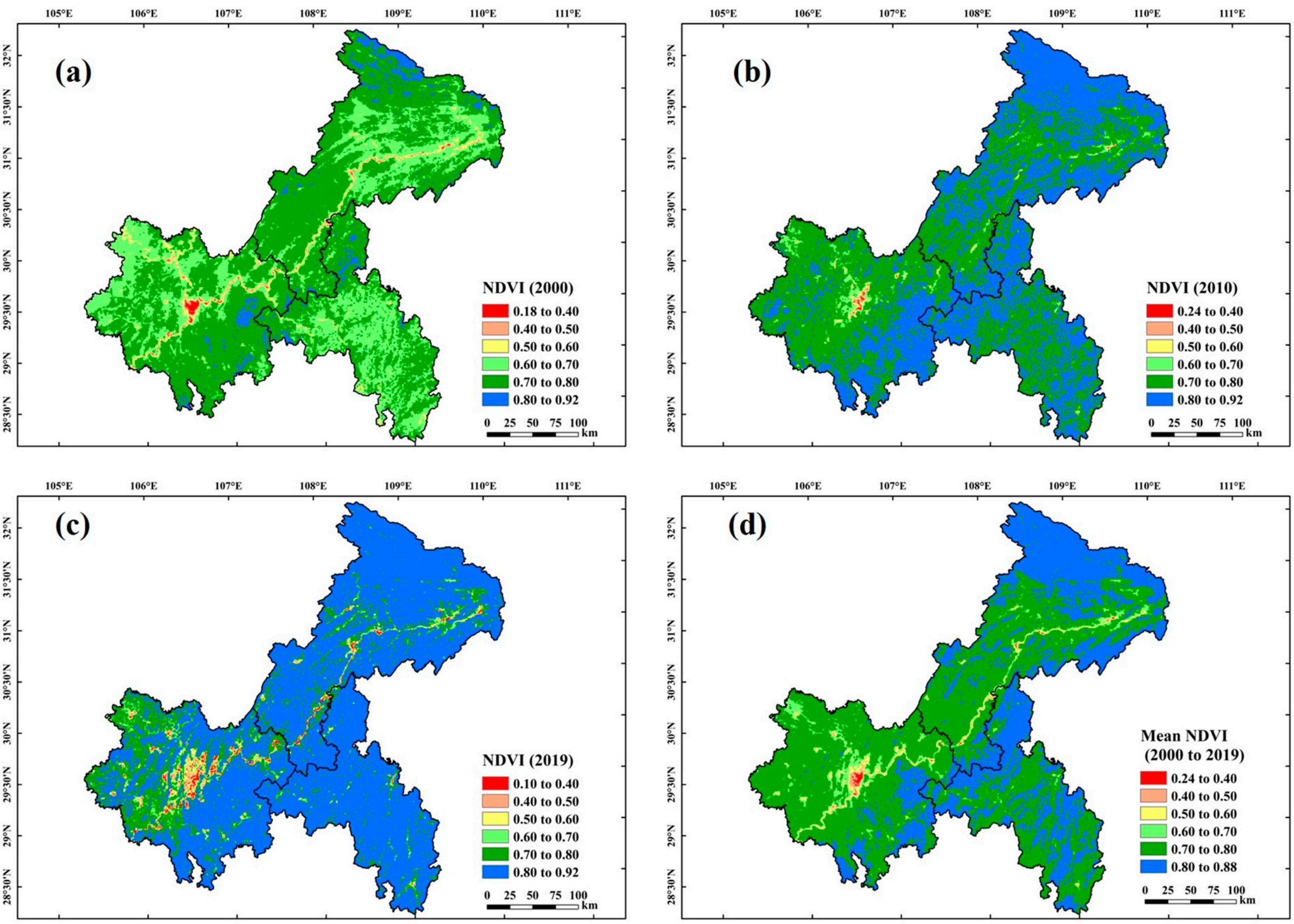

Figure 3. Spatial distribution of vegetation NDVI in Chongqing, China: (**a**) in 2000, (**b**) in 2010, (**c**) in 2019, and (**d**) for the entire 20-year study period of 2000–2019.

Table 3. Spatial distribution characteristics of vegetation NDVI in Chongqing, China, from 2000 to 2019.

Year	2000		2010		2019		2000–2019	
NDVI	Area (km^2)	Proportion (%)	Area (km^2)	Proportion (%)	Area (km^2)	Proportion (%)	Area (km^2)	Proportion (%)
<0.4	214	0.26	49	0.06	575	0.7	361	0.44
0.4–0.5	634	0.77	140	0.17	1008	1.22	374	0.45
0.5–0.6	1912	2.32	326	0.40	1239	1.5	−672	−0.82
0.6–0.7	26,547	32.22	2032	2.47	2619	3.18	−23,928	−29.04
0.7–0.8	49,430	59.99	42,332	51.37	14,431	17.51	−34,999	−42.48
>0.8	3665	4.45	37,523	45.54	62,530	75.88	58,865	71.43

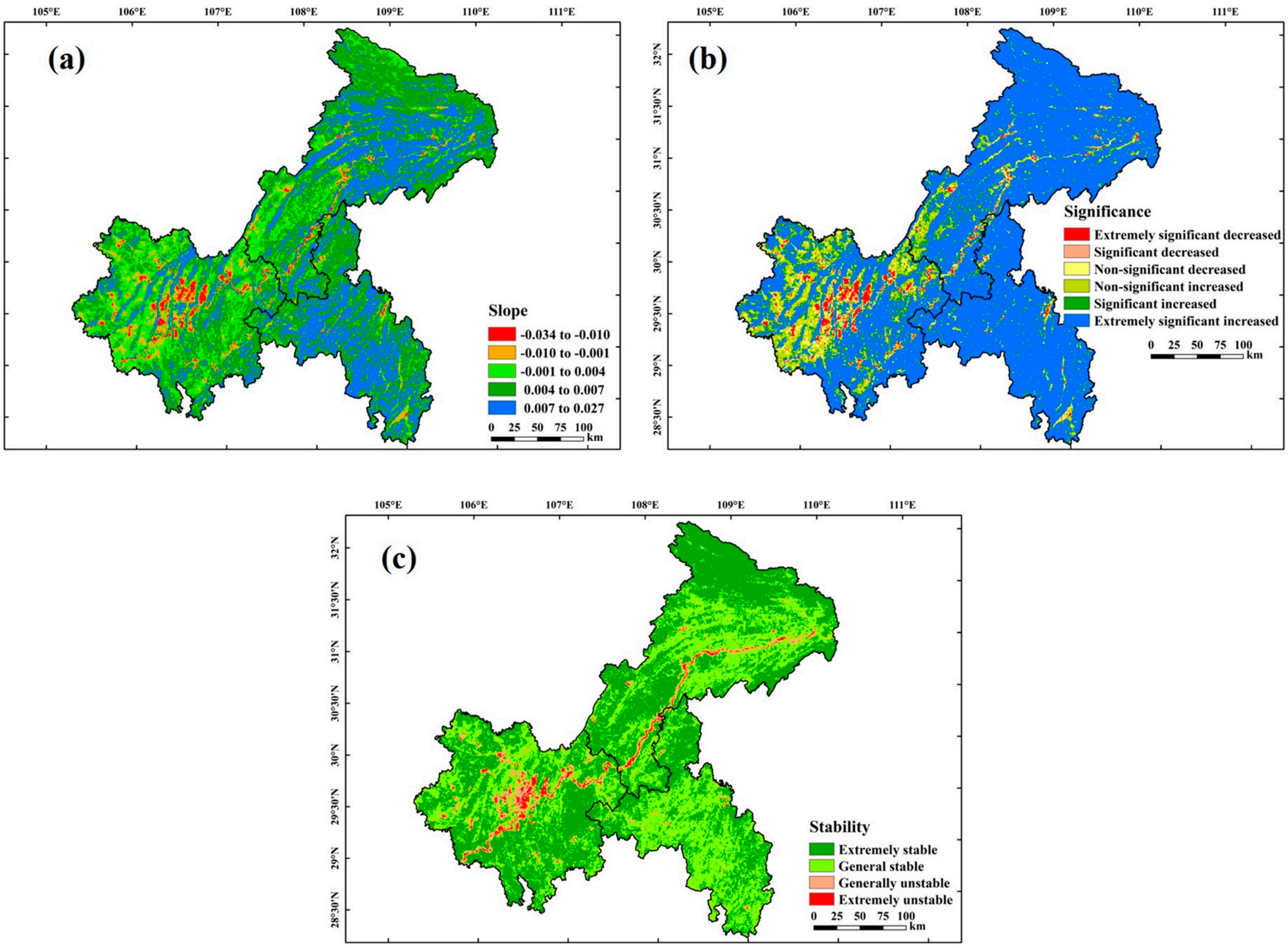

Figure 4. Spatial distributions for (**a**) slope in changing vegetation NDVI dynamics, and their (**b**) significance testing and (**c**) stability analysis, in Chongqing, China, over the entire study period of 2000 to 2019. Notes: we define the significance level as follows: $p < 0.01$ represents extremely significant; $p < 0.05$ represents significant.

Table 4. The slope, significance, and stability of vegetation NDVI in Chongqing, China, from 2000 to 2019.

Type	Range	MCA	TRG	WMA	Chongqing
Slope	−0.034 to −0.010	3.36%	0.62%	0.31%	1.49%
	−0.010 to −0.001	7.93%	2.26%	1.44%	4.03%
	−0.001 to 0.004	35.88%	16.84%	8.36%	21.40%
	0.004 to 0.007	37.67%	49.23%	47.08%	44.71%
	0.007 to 0.027	15.17%	31.05%	42.80%	28.37%
Significance	Extremely significant decrease	4.40%	0.76%	0.43%	1.94%
	Significant decrease	1.65%	0.49%	0.32%	0.85%
	Non-significant decrease	8.29%	2.37%	1.52%	4.22%
	Non-significant increase	22.26%	6.67%	3.56%	11.32%
	Significant increase	10.74%	4.80%	3.23%	6.48%
	Extremely significant increase	52.65%	84.90%	90.95%	75.19%
Stability	Extremely stable	52.54%	57.37%	42.74%	52.19%
	Generally stable	38.03%	39.12%	56.10%	42.82%
	Generally unstable	6.65%	2.59%	0.99%	3.61%
	Extremely unstable	2.78%	0.92%	0.17%	1.38%

Notes: MCA, the major city metropolitan area; TGR, the Three Gorges Reservoir Area town cluster in northeast Chongqing; WMA, the Wuling Mountain Area town cluster in southeast Chongqing. We define the significance level as follows: $p < 0.01$ represents extremely significant; $p < 0.05$ represents significant.

3.3. Single-factor driven analysis

By using the factor detection module, each factor's q statistic was generated to uncover its relative impact on changing vegetation dynamics (Table 5). These results revealed differential impacts of numerous factors among Chongqing as a whole and its three sub-regions, MCA, WMA, and TGR. In the MCA, vegetation change was most influenced by night light brightness (NLB, 0.406), population density (POP, 0.302), atmospheric pressure (PRS, 0.263), and elevation (ELE, 0.258); accordingly, this implied it was mainly affected by human activities and topography. In the TGR, vegetation change was best explained by air temperature (TEM, 0.544), atmospheric pressure (PRS, 0.536), ground temperature (GST, 0.529), and elevation (ELE, 0.511), suggesting it was mainly affected by climate and topography. In the WMA, vegetation change was mainly affected by air temperature (TEM, 0.330), ground temperature (GST, 0.330), PRS (atmospheric pressure, 0.328), and relative humidity (RHU, 0.308), indicating climate was largely responsible.

Table 5. The q statistics value of driving factors of changing vegetation NDVI dynamics in Chongqing, China, at different scales.

Category	Variable	Abbrev.	MCA	TRG	WMA	Chongqing
Climate	Annual average precipitation	PRE	0.121 **	0.363 **	0.102	0.303 **
	Annual average evaporation	EVP	0.104 **	0.453 **	0.220 **	0.297 **
	Annual average relative humidity	RHU	0.188 **	0.171 **	0.308 **	0.168 **
	Annual average air temperature	TEM	0.258 **	0.544 **	0.33 **	0.470 **
	Annual average ground temperature	GST	0.243 **	0.529 **	0.33 **	0.457 **
	Annual sunshine hours	SSD	0.013	0.255 **	0.121 **	0.150 **
	Annual average atmospheric pressure	PRS	0.263 **	0.536 **	0.328 **	0.458 **
Soil	Soil type	SOT	0.089 **	0.260 **	0.090	0.227 **
	Soil sand content	SSAC	0.053 **	0.200 **	0.043	0.152 **
	Soil silt content	SSIC	0.092 **	0.099 **	0.084	0.092 **
	Soil clay content	SCLC	0.071	0.163 **	0.101	0.153 **
Vegetation	Vegetation type	VET	0.059 *	0.109 **	0.061	0.148 **
Topography	Elevation	ELE	0.258 **	0.511 **	0.287 **	0.444 **
	Slope degree	SLD	0.148 **	0.135 **	0.069	0.214 **
Human activity	Land use type	LUT	0.215 **	0.206 **	0.101	0.234 **
	Gross domestic product	GDP	0.186 **	0.096	0.092	0.197 **
	Population density	POP	0.302 **	0.296 **	0.270 *	0.370 **
	Night light brightness	NLB	0.406 **	0.187 **	0.139	0.519 **

Notes: * and ** indicate significant coefficients at $p < 0.05$ and $p < 0.01$, respectively. MCA, the major city metropolitan area; TGR, the Three Gorges Reservoir Area town cluster in northeast Chongqing; WMA, the Wuling Mountain Area town cluster in southeast Chongqing.

For Chongqing's territory, each factor's level (q value) of influence upon the NDVI weakened in this descending rank order: NLB (0.519), TEM (0.470), PRS (0.458), GST (0.457), ELE (0.444), POP (0.370), PRE (0.303), EVP (0.297), land use type (LUT, 0.234), soil type (SOT, 0.227), slope degree (SLD, 0.214), GDP (0.197), RHU (0.168), soil clay content (SCLC, 0.153), soil sand content (SSAC, 0.152), SSD (0.150), vegetation type (VET, 0.148), and soil silt content (SSIC, 0.092). Evidently, a mix of human activities, climate, and topography were the key factor variables that drove the changing vegetation dynamics of Chongqing, whereas the influence of soil and vegetation factors was relatively weak.

3.4. Two-Factor Driven Analysis

By using the interaction detector module, it was possible to calculate how all paired variables could affect changing vegetation dynamics (Table 6). We discovered that the factors influencing vegetation in Chongqing interacted in three different ways: via single-factor nonlinear weakening, nonlinear enhancement, and two-factor enhancement. Among all pairwise interactions, 159 pairs (92.9%) showed two-factor enhancement, indicating this form predominantly drove spatio-temporal changes in vegetation in a complex manner, being affected by the interaction of many factors.

Table 6. Interaction detector results for 18 influencing factors (variables) of changing vegetation NDVI dynamics in Chongqing, China.

Factors	PRE	EVP	RHU	TEM	GST	SSD	PRS	SOT	SSAC	SSIC	SCLC	VET	ELE	SLD	LUT	GDP	POP	NLB
PRE	0.303																	
EVP	0.400	0.297																
RHU	0.403	0.412	0.168															
TEM	0.492	0.490	0.488	0.470														
GST	0.478	0.483	0.480	0.472	0.457													
SSD	0.367	0.381	0.447	0.484	0.473	0.150												
PRS	0.489	0.484	0.478	0.477	0.472	0.476	0.458											
SOT	0.365	0.382	0.322	0.478	0.464	0.292	0.472	0.227										
SSAC	0.353	0.350	0.285	0.480	0.469	0.247	0.470	0.259	0.152									
SSIC	0.355	0.359	0.256	0.486	0.474	0.261	0.473	0.275	0.232	0.091								
SCLC	0.348	0.351	0.282	0.483	0.469	0.260	0.470	0.249	0.232	0.180	0.153							
VET	0.342	0.364	0.265	0.476	0.463	0.277	0.471	0.277	0.229	0.224	0.233	0.148						
ELE	0.478	0.473	0.471	0.486	0.479	0.463	0.475	0.460	0.458	0.463	0.459	0.459	0.444					
SLD	0.387	0.400	0.366	0.491	0.479	0.288	0.481	0.316	0.273	0.273	0.280	0.284	0.472	0.214				
LUT	0.430	0.441	0.369	0.545	0.532	0.347	0.532	0.362	0.323	0.317	0.320	0.306	0.526	0.351	0.234			
GDP	0.424	0.419	0.337	0.551	0.539	0.310	0.541	0.357	0.320	0.271	0.314	0.296	0.529	0.340	0.333	0.197		
POP	0.496	0.498	0.447	0.558	0.546	0.444	0.549	0.423	0.412	0.409	0.404	0.395	0.542	0.414	0.416	0.408	0.370	
NLB	0.551	0.536	0.473	0.627	0.619	0.452	0.627	0.495	0.463	0.429	0.458	0.434	0.619	0.484	0.478	0.419	0.530	0.519

Notes: Blue represents a two-factor enhancement, green represents a non-linear enhancement, and orange represents a single-factor non-linear reduction. More information can be found in Table 2. For details about the factor abbreviations, please see Table 1.

The average value of each interacting factor was next examined. The factor's level (q value) of influence on the NDVI weakened in this descending rank order: ELE (0.522), NLB (0.519), TEM (0.504), PRS (0.502), GST (0.495), POP (0.450), EVP (0.419), PRE (0.415), RHU (0.371), LUT (0.365), SLD (0.361), GDP (0.341), SOT (0.336), VET (0.332), SSD (0.328), SCLC (0.328), SSAC (0.309), and SSIC (0.295). This demonstrated that although soil type and vegetation type can exert some influence, it was still minor compared to human activities, climatic variables, and topographic conditions. Within these similar categories, the strongest prevailing interactions were found for the paired variables: POP ∩ NLB (0.530), TEM ∩ PRE (0.492), SLD ∩ ELE (0.472). Overall, however, between differing types of factors, the strongest dominant interaction factors were the TEM ∩ NLB (0.627), PRS ∩ NLB (0.627), and ELE ∩ NLB (0.619). We found that interactions between differing types of factors were stronger than those arising between similar ones.

3.5. Ecological Detector Analysis

Whether the effects of interactions between two factors on vegetation NDVI differ significantly can be evaluated using the ecological detector module. As seen in Table 7, there were significant differences ($p < 0.05$) in the explanatory power of nearly half (46.4%) of the factor combinations for NDVI. The following scenarios exhibited notable variation in how two factors affected the geographical differentiation of changing vegetation NDVI dynamics in Chongqing: among all climatic variables, TEM ∩ factors (PRE, EVP, RHU), GST ∩ factors (PRE, EVP, RHU), PRS ∩ factors (PRE, EVP, RHU, SSD); among all soil variables, SOT ∩ factors (RHU, SSD), SCLC ∩ SSIC; in the vegetation variables, VET and SSIC; among all human activities variables, LUT ∩ factors (RHU, SSD, SSAC, SSIC, SCLC, VET, SLD), GDP ∩ factors (RHU, SSD, SSAC, SSIC, SCLC, VET), POP ∩ factors (PRE, EVP, RHU, SSD, SOT, SSAC, SSIC, SCLC, VET, SLD, LUT, GDP), NLB and all factors. Additionally, there was no discernible difference between the impacts of the other interactions between two factors on the NDVI's regional differentiation across Chongqing.

Table 7. Statistical tests of 18 influencing factors of changing vegetation NDVI dynamics in Chongqing, China, based on the ecological detector module (significant at $p < 0.05$).

Factors	PRE	EVP	RHU	TEM	GST	SSD	PRS	SOT	SSAC	SSIC	SCLC	VET	ELE	SLD	LUT	GDP	POP	NLB
PRE																		
EVP	N																	
RHU	N	N																
TEM	Y	Y	Y															
GST	Y	Y	Y	N														
SSD	N	N	N	N	N													
PRS	Y	Y	Y	N	N	Y												
SOT	N	N	Y	N	N	Y	N											
SSAC	N	N	N	N	N	N	N	N										
SSIC	N	N	N	N	N	N	N	N	N									
SCLC	N	N	N	N	N	N	N	N	N	Y								
VET	N	N	N	N	N	N	N	N	N	Y	N							
ELE	Y	Y	Y	N	N	Y	N	Y	Y	Y	Y	Y						
SLD	N	N	Y	N	N	Y	N	N	Y	Y	Y	Y	N					
LUT	N	N	Y	N	N	Y	N	N	Y	Y	Y	Y	N	Y				
GDP	N	N	Y	N	N	Y	N	N	Y	Y	Y	Y	N	N	N			
POP	Y	Y	Y	N	N	Y	N	Y	Y	Y	Y	Y	N	Y	Y	Y		
NLB	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	

Notes: The 'Y' indicates significant difference in the effects of the two factors on changed vegetation NDVI, whereas the 'N' denotes no significant difference detected. For information about the factor abbreviations, please refer to Table 1.

3.6. Types or Range of Suitable Influencing Factors

We presumed that the factor of type or range with a higher NDVI would be better suited for vegetation growth when the risk detector assesses how vegetation changes in response to various factors. As seen in Table 8, in terms of meteorological conditions, PRE, RHU, and SSD tended to increase as the interval increased, whose most suitable ranges were 1538~1682 mm, 81.9%~84.5% and 1526~1646 h, respectively. Conversely, EVP, TEM, GST, and PRS tended to decrease as the interval increased, for which the most suitable range was 640~715mm, 4.7~7.8 °C, 7.3~10.4 °C, 742~802 hPa.

Table 8. The suitable range or type of 18 factors influencing the changing vegetation NDVI dynamics in Chongqing, China.

Category	Variable	Abbrev.	Units	Suitable Range or Type	NDVI Mean
Climate	Annual average precipitation	PRE	mm	1538 to 1682	0.851
	Annual average evaporation	EVP	mm	640 to 715	0.847
	Annual average relative humidity	RHU	%	81.9 to 84.5	0.833
	Annual average air temperature	TEM	°C	4.7 to 7.8	0.856
	Annual average ground temperature	GST	°C	7.3 to 10.4	0.855
	Annual sunshine hours	SSD	hour	1526 to 1646	0.855
	Annual average atmospheric pressure	PRS	hPa	742 to 802	0.854
Soil	Soil type	SOT	-	Semi-leached soil	0.842
	Soil sand content	SSAC	%	33 to 34	0.85
	Soil silt content	SSIC	%	38 to 42	0.835
	Soil clay content	SCLC	%	12 to 16	0.84
Vegetation	Vegetation type	VET	-	Broad-leaved forest	0.828
Topography	Elevation	ELE	m	2000 to 2624	0.854
	Slope degree	SLD	°	39.2 to 56.2	0.824
Human activity	Land use type	LUT	-	Woodland	0.808
	Gross domestic product density	GDP	10^4 Yuan/km^2	0 to 1954	0.788
	Population density	POP	persons/km^2	0 to 143	0.809
	Night light brightness	NLB	DN	0 to 1.6	0.793

In terms of soil conditions, the most suitable SOT was semi-leached soil, and the most suitable ranges for SSAC, SSIC and SCLC were 33%~34%, 38%~42%, and 12%~16%, respectively. In terms of vegetation types, it was most suitable to grow broad-leaved forest. Regarding topography, across Chongqing, NDVI increased with the SLD and ELE, these being most suitable in the range of 39.2~56.2° and 2000~2624 m, respectively.

In terms of human activities, woodlands were the most conducive land use type for vegetation growth, and the NDVI was highest in areas with low GDP, POP, and NLB, meaning that these were most suitable when in the range 0~1954 $\times 10^4$ Yuan/km^2, 0~143 person/km^2, and 0~1.6 DN.

4. Discussion

4.1. NDVI's Spatio-Temporal Changes

The results of this study demonstrated an upward trend in the vegetation NDVI in Chongqing between 2000 and 2019 (Figure 2), with its vegetation conditions found greatly improved at various temporal and geographical scales (Figure 4). These recovery areas, mainly situated in the southeast and northeast parts of Chongqing, together expanded to 75.19% of its territory from 2000 to 2019, a result consistent with the findings of Xiao et al. [45] and Zhang et al. [23]. This may be attributed to the ecological conservation projects implemented by the government. For example, based on Landsat and MODIS data, Li et al. [46] showed that ecological engineering measures in the Three Gorges Reservoir area, such as the ecological migration project, the ecological protection and restoration project, and Grain for Green, played a positive role in ecological restoration and effectively improved local vegetation coverage. Li Z. and Li X. [47] reported that human activities, such as agricultural production, cultivated land protection, and vegetation ecological construction, were the primary factors responsible for vegetation growth and expansion in Chongqing. Work by Liu et al. [48] quantified the relative contribution rates of human activities and climate to vegetation change in Chongqing as 90.96% and 9.04%, respectively, revealing the overwhelmingly dominant role of human activities. Those areas with significant degradation and instability of vegetation NDVI are mainly concentrated in the major metropolitan area, near water, and some surrounding areas (Figure 4), a pattern basically consistent with the findings of Zhu et al. [49]. According to Li et al., the expansion of human urban construction land across the world's cities is the main reason for the downward trend of regional vegetation NDVI, and the process of urbanization is directly and indirectly having adverse impacts on global urban vegetation growth [50,51].

4.2. NDVI Response to Driving Factors

Previous research has demonstrated that both natural and human activities can distort and modulate the temporal and spatial variation in vegetation dynamics [15,38], making it difficult to investigate the mechanisms underlying the spatial heterogeneity of vegetation [34]. We found that the interaction of most dual-factor variables increased their degree of influence on vegetation change, the latter often affected by the interaction of multiple factors (Table 6). In short, the interaction of two factors is more important to vegetation change than each factor alone, an outcome consistent with previous studies [15,38,52]. Therefore, when considering the change of NDVI, we need to fully consider the interaction between factors. For example, we found that the suitable range of annual mean temperature for vegetation growth in the Chongqing area is 4.7–7.8 °C (Table 8), which was located at higher altitudes (Figure A1, TEM and ELE). Therefore, it is actually a trade-off considering multiple factors, rather than the most suitable temperature for plant physiology. This may be closely related to our hypothesis that the range of factors affecting the maximum NDVI value was the range of the most suitable growth factors.

Our results suggest that the effects of human activity on vegetation change should not be disregarded (Table 5). The explanatory power of nocturnal light brightness (NLB) for vegetation change reached as high as 51.9% (Table 5), confirming that human activities heavily impact changing vegetation dynamics in Chongqing and are of paramount concern.

These findings are in line with those of Liu et al. [48], who estimated that human activities contributed as much as 90.96% to vegetation change in Chongqing. In general, there is a positive correlation between NLB and socio-economic factors, meaning that NLB can effectively express the intensity of human activities such as urbanization level, population density, and GDP [53,54]. Indeed, human driving factors, both population density and GDP, often emerge as the dominant ones affecting regional vegetation change. For example, Sun et al. [55] found that agricultural vegetation NDVI is very sensitive to economic as well as population growth, which may lead to changes in vegetation NDVI in Chongqing given its extensive distribution of cultivated land (Figure 2). Herrero et al. [56] reported a significant negative correlation between population density and NDVI around Southern African national parks during the 21st century (2000–2016). We found that NDVI tends to be augmented in woodland, and by a lower GDP, POP, and NLB (Table 8). This may be due to sparse and small populations and small-scale economies in certain areas, which are less apt to incur damage to vegetation from humans. This suggests trade-offs likely loom between future ecological and economic development, but devising sustainable human interventions may contribute to promoting vegetation recovery and diversity, thereby restoring the ecological balance in the study area.

Climatic factors are generally considered critical to the growth and distribution of vegetation [57,58]. Among these, we found that the explanatory power of annual mean temperature, annual mean pressure, annual mean ground temperature and annual mean precipitation for vegetation change weakened in that order (Table 5). Hence, the influence of air temperature on changing vegetation dynamics in the studied region was greater than that of precipitation. These results are consistent with those of Zhang et al. [59] and Liu et al. [60], and can be explained by Chongqing's location in the upper reaches of the Yangtze River and the central zone of the Three Gorges Reservoir Area. The water needed for vegetation growth here is sufficient, so temperature probably becomes a more pertinent factor than precipitation in modulating vegetation growth and dynamics. Under the premise of sufficient rainfall, a rising temperature can enhance plant photosynthesis, which should favor the growth of most plant species. However, the influence of climatic factors on the changing dynamics of vegetation growth often harbors a threshold effect [61–63]. For example, in Chongqing, the area with sufficient precipitation and annual sunshine duration will most favor the growth of its vegetation, while the area with higher temperature and increased evaporation is more likely to limit that growth in vegetation (Table 8). This may be attributed to the humid subtropical monsoon climate of Chongqing, which has hydrothermal conditions suitable for growing vegetation. When at a low level, temperature often becomes a limiting factor for the plant's physiological processes; hence, an appropriate temperature rise can promote photosynthesis and accelerate the absorption of soil nutrients, thus promoting the growth of vegetation [64]. However, once temperatures exceed the tolerable range of plant species, extreme heat increases transpiration and respiration rates, which accelerate dry matter consumption and soil water losses, leading to reduced photosynthesis and nutrient uptake and transport, which is clearly detrimental to vegetation growth [65].

In terms of topography, with an increase in elevation or slope, the vegetation NDVI in Chongqing gradually increased as well in tandem (Table 8), a trend consistent with the study by Zhu et al. [66], who found that Chongqing had a high vegetation coverage in those areas at high elevations (>1200 m) and with steeper slopes (>15°). Our study showed that ELE explained 44.4% of the vegetation change, likely because it determines the flow and stability of surface materials, modulates the spatial distribution of air temperature and water, and alters vegetation dynamics via temperature, precipitation, soil moisture, soil nutrients, and other factors [67–69]. In fact, temperature tends to have a greater effect on vegetation growth at higher elevations than at lower elevations. For example, Pan et al. [70] used Landsat NDVI and climate data from 1992 to 2020 to explore the impact of topography on vegetation change on the Qinghai-Tibet Plateau. Their results showed that precipitation had a greater impact than air temperature upon vegetation growth in the region lying below 3000 m, and vice versa in the region above 3000 m. Thus, in high-elevation areas, temperature may be the main factor limiting the growth of vegetation [71]; low temperatures often limit the growth of plants by reducing their photosynthesis, soil nutrient absorption rate, and delaying key phenological events, among other impacts [72]. In addition, with rising elevation, the corresponding reduced water availability may also limit vegetation recruitment and growth.

4.3. Caveat and Future Work

Vegetation dynamics are closely related to a variety of factors [37,38,70]. Although this work fully considered the impact of 18 influencing factors, including climate, soil, vegetation, topography, and human activities, upon vegetation change, which helps to further improve our understanding of its driving mechanism, some limitations and uncertainties persist. In terms of method, these are as follows. (1) We found that elucidating the driving mechanisms of vegetation dynamics depends on spatial scale, so we need to consider further the main vegetation drivers involved at multi-scale spatial scales to further reduce the uncertainty concerning how they impact vegetation dynamics. (2) Although Geodetector has realized the measurement, significance test, and attribute analysis of spatial differentiation, it also has limitations in discussing the interactions with temporal vegetation dynamics. (3) The most significant of these is that it cannot simultaneously evaluate the joint influence of multiple variables on changing dynamics of vegetation. Therefore, in future work, we plan to explore the nonlinear driving mechanism of multiple factors on vegetation dynamics. In terms of method, among the 18 variables, the non-time variable data (vegetation type, soil type, soil sand content, soil silt content, soil clay content, elevation, slope degree, etc.) is often difficult to change in a certain period of time, which makes it difficult to understand the driving mechanism of NDVI change from the perspective of time change.

5. Conclusions

This study illustrated the dynamic trends in NDVI's temporal and geographical variability in Chongqing from 2000 through 2019. We discovered that whereas the majority of Chongqing's vegetation recovery area—75.19%—was located in the WMA and TRG, the majority area of the vegetation degradation and lower stability was located within the MCA. As a result, in the future, we need to concentrate on and increase vegetation management and restoration in the MCA. The influencing factors associated with human activities, climate, and topography upon changing vegetation dynamics cannot be ignored. Among all 18 factors considered, NLB (51.9%), TEM (47%), PRS (45.8%), GST (45.7%), ELE (44.4%), POP (37%), and PRE (30.3%) were the main single factors affecting vegetation change, and the relative impacts on vegetation change gradually lessened. We discovered that it was most often (92.9% of all cases) achieved by synergetic interactions between factors (two-factor enhancement)—that is, the combination of two factors has a greater impact on vegetation change than either single component has, and the interaction of differing factors has a greater impact than that of similar factors. For Chongqing, we were able to discern the range of favorable meteorological conditions, adequate precipitation, and yearly sunshine hours that promote vegetation growth there, whereas increased evaporation and rising temperature were more likely to hinder it. In terms of terrain, the Chongqing area's NDVI steadily rises with increasing elevation and slope. In terms of human activity, those areas in the woods and with lower GDP, POP, and NLB were more favorable for sustaining vegetation growth and dynamics. These results could serve as a foundation for improving the management and regeneration of vegetation in the upper parts of the Yangtze River Basin.

Author Contributions: Conceptualization: X.G., B.Y. and S.L. Methodology: X.G., B.Y. and L.M. Software: X.G., X.W. and B.Y. Formal analysis, X.G., B.Y., L.M., X.W. and S.L. Resources: L.M. and H.S. Data curation: X.G. Writing—original draft preparation: B.Y., L.M., X.G. and X.W. Writing—review and editing: X.G., B.Y. and X.W. Visualization: X.W. Supervision: X.G. and X.W. All authors have read and agreed to the published version of the manuscript.

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

Appendix A

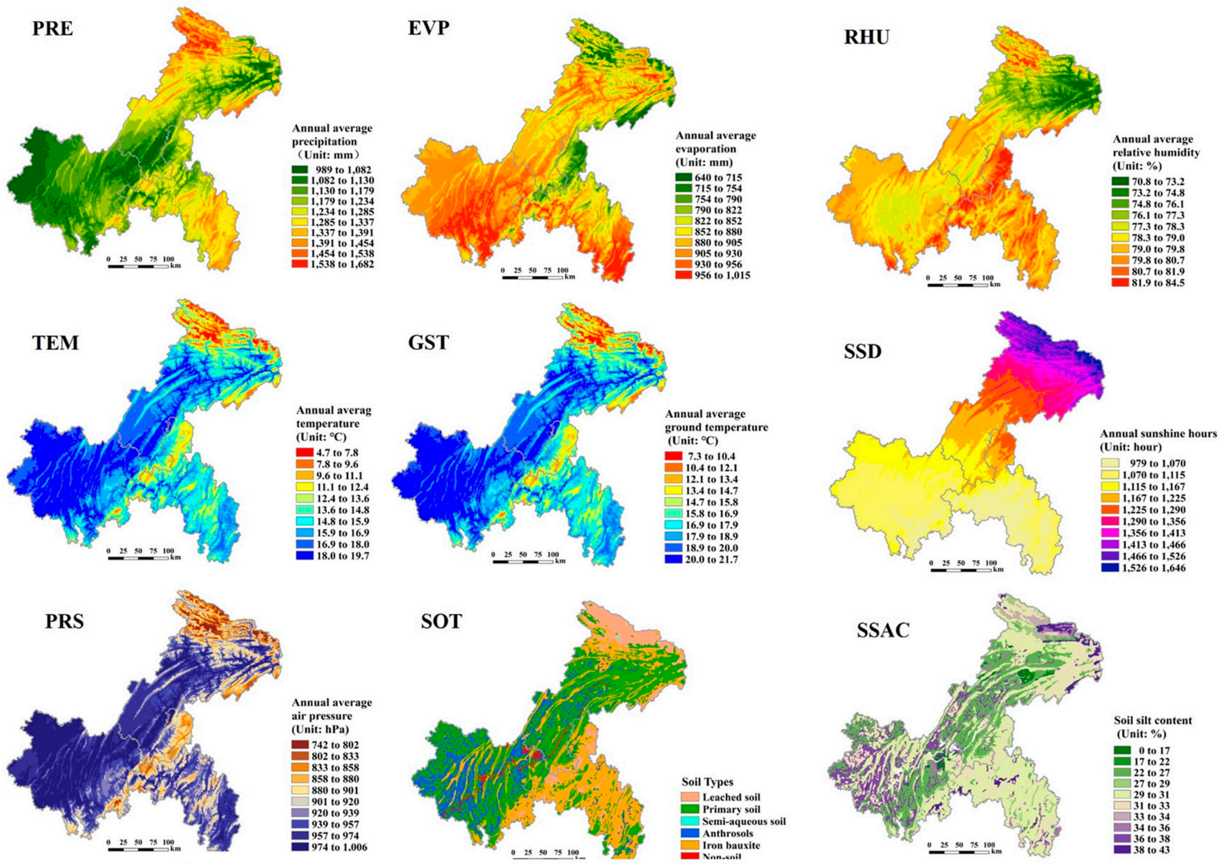

Figure A1. *Cont.*

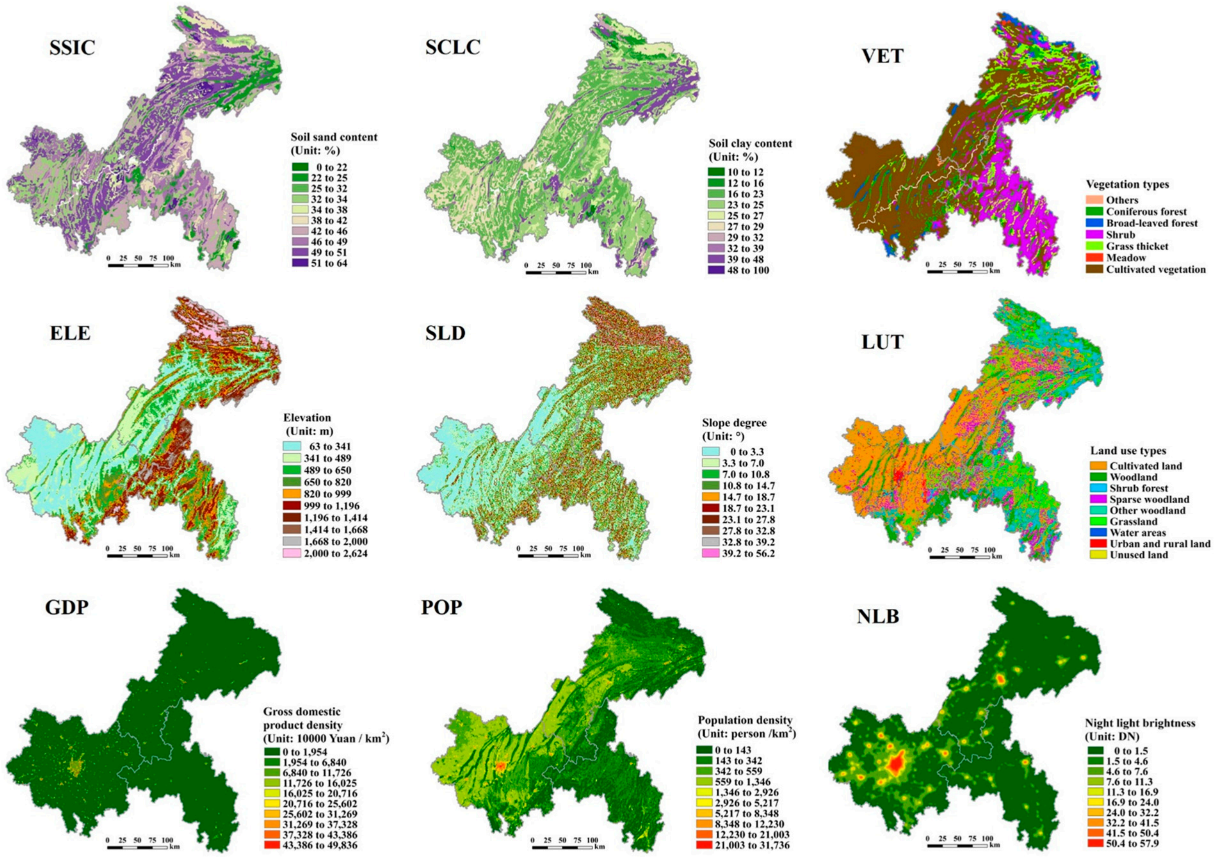

Figure A1. Spatial distributions of all 18 influencing factors (variables) in Chongqing, China. Their abbreviations are detailed in Table 1.

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