How Did the Mild and Humid Areas of China Turn Green? A Case Study on Chongqing

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Abstract: Since the implementation of the Natural Forest Resources Protection Project (NFRP) and the Grain for Green Program (GFGP), two key ecological projects related to forestry, the vegetation cover in Chongqing, has improved significantly. Existing studies have revealed the effects of climate change and human activity on vegetation cover in arid regions. However, more studies are needed to reveal the influence of drivers on vegetation cover in mild and humid areas, to quantify the relative contribution of drivers and to analyze the overall land use characteristics in different regions. In this study, we used Theil–Sen slope analysis and the Mann–Kendall test to investigate the spatial and temporal changes in vegetation cover in Chongqing. Further, we used Pearson correlation analysis to analyze the correlations between vegetation cover and drivers, quantitatively analyzing the relative contributions of these drivers. Complex network model analysis was used for different regions to obtain their land-use system characteristics, and the Hurst index was adopted to predict future vegetation-cover changes. The results of this study showed that the average vegetation cover in Chongqing increased significantly from 2000 to 2020, and the overall greening trend was most obvious in winter. Precipitation and temperature influenced the vegetation cover of Chongqing city to a certain extent, and the positive correlation between vegetation cover and precipitation was more significant than that with temperature. In terms of the precipitation factor, the areas with significant positive correlations were mainly concentrated in the central and southern parts of Chongqing, which could be related to the higher precipitation in the southern part of the city. Under the combined influence of climate change and human activity, vegetation cover increased in 71.95% of the total area. Human activity had a relative contribution of 70.39% and 69.14% in the areas where vegetation cover decreased and increased, respectively. The analysis results of the complex network model showed that woodlands and grasslands contributed more to areas where the vegetation cover exhibited an increasing trend. In the future, it is estimated that 72.92% of the vegetation cover in Chongqing will exhibit a degradation trend. This study helps us further understand vegetation-cover changes in mild and humid areas, providing new research directions for informing forestry-related policies.

Keywords: vegetation cover; spatiotemporal changes; residual trend analysis; complex network model; relative contribution; forestry-related ecological policies

1. Introduction

Vegetation plays an important role in terrestrial ecosystems as a link between solar energy and bioenergy, influencing the climate, water cycle, and carbon cycle [1]. Studies related to vegetation-cover changes have attracted significant research attention in several fields [2]. Different vegetation distribution patterns will lead to the formation of different ecological landscapes, and vegetation changes that occur due to natural or human influences will have certain effects on the original ecosystem [3,4]. Therefore, research on the trends of vegetation-cover changes and their driving forces is necessary to inform
both researchers and policymakers, allowing them to understand the factors affecting
vegetation-cover changes. This can help protect the ecological environment scientifically
and effectively [5].

In recent years, remote sensing has become an important technique for vegetation
monitoring [6]. In particular, the normalized difference vegetation index (NDVI) has been
developed, which can reflect vegetation growth and has been widely used to analyze
vegetation-cover changes. There are many platforms that provide NDVI datasets acquired
by sensors, such as MODIS and GIMMS, which allow researchers to obtain time-series-
continuous and large-scale datasets [7]. It has been shown that vegetation-cover changes
are influenced by a combination of natural factors and human activities [3,8]. Natural
factors—such as the temperature, precipitation, soil, and topography—can change the
spatial distribution of vegetation cover [9–12]. In particular, temperature and precipitation
can directly influence the water cycle and energy conversion, and are the main climatic
factors affecting vegetation-cover changes [13–16]. At high altitudes, increases in temper-
ature facilitate photosynthesis, extending the growing season [17]. Temperature can also
negatively affect vegetation cover if it exceeds the optimum temperature for vegetation
growth [18]. Precipitation is another important climatic factor affecting vegetation cover,
influencing the activity of roots by affecting soil moisture [19]. However, the effect of the
combination of precipitation and temperature on vegetation-cover changes exhibited strong
spatial heterogeneity. For example, in drier areas, more precipitation has a positive effect on
vegetation cover, and is a key factor affecting growth [20]. Precipitation can also negatively
affect vegetation cover in some areas. Wu et al. studied Guangdong Province, which
experiences a warm and humid climate, and concluded that vegetation-cover changes were
negatively correlated with precipitation due to extreme and severe precipitation events [21].
Most existing studies on the effects of water and heat on vegetation-cover changes have
focused on arid and semi-arid regions, where vegetation cover is highly dependent on
precipitation [22–24]. Chongqing experiences a mild and humid subtropical climate, with
sufficient precipitation. Therefore, to obtain knowledge on the climatic factors affecting
vegetation cover in mild and humid regions, Chongqing city is taken as an example. Fur-
furthermore, predicting future vegetation cover is of great significance to the Chongqing
Municipality, and can provide a basis for the formulation of relevant government policies.

In addition to climatic factors, the influence of anthropogenic factors on vegetation
cover has become more obvious over a long time scale, as human activities such as urban
expansion and ecological restoration continue to intensify [25]. Xiu et al. found that
vegetation cover in the Hongjian Nur region is less influenced by climatic factors, with
human activities—such as agricultural irrigation—being the main drivers [26]. Baniya et al.
determined the role of the climate in vegetation-cover changes in Nepal through Pearson
correlation analysis [27]. Nanzad et al. analyzed the correlation between changes in NDVI
anomalies and climatic factors in Mongolia [28]. At the same time, afforestation is a human
activity that can result in large-scale changes in vegetation cover [29,30]. A series of large-
scale human activities that have a positive impact on vegetation cover are usually supported
by government policies, where forestry-related ecological conservation projects can direct
social resources to participate in ecological conservation and thus increase vegetation
cover [30]. Initiatives to reduce forest degradation have led many countries to place greater
emphasis on forest conservation and ecologically sustainable development [31,32]. Global
restoration movement promoted by some countries and multilateral organizations have
restoration of damaged forest land as one of their goals, such as the Aichi Targets and
New York Declaration on Forests [33,34]. The Chinese government has also implemented
a series of key ecological projects related to forestry, thereby positively impacting the
regional ecological environment [35]. The Natural Forest Resources Protection Project
(NFRP), a world-renowned ecological project, was piloted in 1998 and its main measure
was to prohibit the cutting of natural forests and afforestation on barren lands. This
policy has led to an increase in total forest resources and a restructuring of the forest
economy. The Grain for Green Program (GFGP) was piloted in Chongqing at the end of
1999 to systematically restore cropland unsuitable for cultivation to woodland or grassland, thereby accelerating erosion control and increasing the greening rate [36,37]. These two projects are the main afforestation policies in Chongqing. Previous studies have generally only conducted correlation analysis between vegetation cover and its drivers [38,39], while the quantitative analysis of the impact of these drivers is less common. In this study, in addition to correlation analysis, the relative contributions of climate change and human activities to vegetation cover were also calculated, facilitating a better understanding of the roles played by the drivers in different regions.

Land-use change has significant effects on vegetation cover, especially in developing countries, which are experiencing extensive and rapid land-use changes [40,41]. Therefore, it is necessary to understand the systemic characteristics of regional land-use change to better understand vegetation-cover changes. However, few extant studies have analyzed the systemic characteristics of land use in different regions based on the trends of vegetation-cover change. Feng et al. analyzed the trends of vegetation-cover change in regions experiencing different land-use type changes through a land-use transfer matrix [39]. Wu et al. analyzed the vegetation-cover changes due to land-use type changes [21]. Further, complex network model can help identify the overall characteristics of network systems, as well as the relationships between nodes. This model has been previously used to analyze the overall land-use system characteristics, and can be used to obtain the key land-use types and overall stability of the land-use system by calculating the betweenness centrality and average shortest path, respectively [42,43]. The aforementioned model has also been used to study language translation and analyze big data [44,45]. However, complex network model has rarely been used for comparative analyses of overall land-use system characteristics in areas with different vegetation-cover change trends. In this paper, Chongqing city is divided into four regions according to different vegetation-cover change trends, and the complex network model is innovatively used to analyze the key land-use types and land-use system stability in different regions; this helps obtain a more comprehensive understanding of regional vegetation-cover changes and analyze the role of forestry-related ecological policies in different regions.

Therefore, our study aims to: (i) analyze the spatial and temporal changes in vegetation cover in Chongqing using Theil–Sen slope analysis and Mann–Kendall tests; (ii) analyze the correlation between vegetation cover and drivers; (iii) quantify the relative contribution of climate change and human activities to vegetation-cover change (iv) analyze the impact of forestry-related ecological policies on vegetation cover using the complex network model and Pearson correlation analysis to investigate the impact of forestry-related ecological policies on vegetation cover, and (v) explore the sustainability and trends of future vegetation-cover changes.

2. Data and Methods

2.1. Study Area

Chongqing is located in southwest China and is an important financial center in the upper reaches of the Yangtze River (Figure 1). Chongqing is the only municipality directly under the central and western regions, with an area of 82,400 square kilometers, and 38 districts and counties under its jurisdiction. It is located in a region that experiences a hot and humid subtropical climate, with an average annual temperature of 16–18 °C. It receives abundant rainfall, with an average annual precipitation of 1000–1350 mm. The population is 32.124 million, and its urbanization rate is over 70%. The terrain is undulating, with the western and central areas being lower and dominated by hills and mountains. The number of good air quality days exceeds 320 days in a year, and the forest coverage rate reaches about 54.5%. In 2021, the gross domestic product (GDP) of the region exceeded CNY 2.7 trillion, which represents an increase of 8.3%, and the per capita disposable income increased by nearly 10% (https://www.cq.gov.cn/zjzq/ (accessed on 6 May 2022)).
2.2. Data Sources and Preprocessing

(i) Google Earth Engine (GEE) is a geographic information visualization and analysis platform that provides users with free, downloadable geographic information data and data analysis algorithms to help easily analyze large amounts of data [46]. The NDVI dataset from 2000 to 2020 was downloaded using GEE, and MOD13Q1 NDVI data were obtained using the JavaScript application programming interface with a temporal resolution of 16 days and a spatial resolution of 250 m for the MOD13Q1 NDVI product. To reduce the effects of errors and cloudiness, we applied the maximum value composite approach to the NDVI dataset. In this paper, March to May is categorized as spring, June to August as summer, September to November as autumn, and December to February as winter.

(ii) Monthly temperature and precipitation datasets were obtained from the National Earth System Science Data Center, National Science and Technology Infrastructure of China (http://www.geodata.cn/, accessed on 6 May 2022) with a spatial resolution of 1000 m, and annual data were obtained by extracting and processing monthly temperature and precipitation data through the Matlab platform. These datasets have been validated with observations from 496 meteorological stations across China from 1951 to 2016 [47,48].

(iii) The land-use cover dataset was downloaded from the Resource and Environment Data Cloud Platform (http://www.resdc.cn, accessed on 6 May 2022) with a spatial resolution of 1000 m. The dataset was reclassified into six land-use types using ArcGIS 10.3: cropland, forest land, grassland, water, built-up land, and unused land.

(iv) Afforestation data were obtained from the China Forestry Statistical Yearbook.

(v) Through ArcGIS 10.3 platform, the
spatial resolution of all raster data was unified to 1000 m, and the coordinate system was unified to Krasovsky_1940_Albers.

2.3. Methods
2.3.1. Research Framework

The NDVI can be used to characterize the degree of vegetation cover and has been widely applied in different fields of study [49–52], so it can be used to represent the vegetation cover in Chongqing. In our study vegetation cover is considered as the value to monitor the degree of vegetation growth. The proportion of bare land in the study area is so small that it is assumed to be negligible, and the NDVI (vegetation cover) of bare land is of research value for determining the ecological change [49]. Therefore, this paper uses the NDVI to study the vegetation cover of Chongqing. The primary object of our study was the “vegetation cover” characterized by NDVI: first, we analyzed the annual and seasonal spatial and temporal variations in vegetation cover; second, we analyzed the correlation between vegetation cover, climatic factors, and human activities; third, the relative contributions of climate change and human activities to vegetation-cover change were quantified; fourth, based on the complex network model and Pearson correlation analysis, we explored the influence of afforestation policies on vegetation cover. We divided Chongqing into four regions based on vegetation cover change trends, and then analyzed the overall land use system characteristics of different regions through a complex network model to obtain the roles played by woodlands and grasslands in different regions, and to further illustrate the role of ecological protection policies related to forestry. The correlation between cumulative afforestation area and vegetation cover was obtained by Pearson correlation analysis; fifth, future vegetation-cover changes were predicted. The research flowchart is shown in Figure 2.

![Figure 2. Flowchart of the research methodology.](image_url)

2.3.2. Maximum Value Compositing

Maximum value compositing is a common compositing method used to process NDVI data. The use of this pre-processing method minimizes the interference produced by...
cloudiness, etc., on the NDVI dataset [53,54]. The specific equation for this technique is as follows:

\[ \text{NDVI}_{\text{max}} = \max(\text{NDVI}_1 + \text{NDVI}_2 + \text{NDVI}_3 + \cdots + \text{NDVI}_i) \]  

(1)

\( \text{NDVI}_{\text{max}} \) is the annual maximum of vegetation cover, \( i \) represents the month, and \( \text{NDVI}_i \) is the vegetation cover in the \( i \)th month.

2.3.3. Theil–Sen Slope Analysis and Mann–Kendall Test

Theil–Sen slope analysis is used to analyze the trends in vegetation-cover changes from 2000–2020, using median values to estimate changes in NDVI and, thus, reducing the adverse effects of anomalous values [55,56]. The Mann–Kendall test is used to ascertain the significance of vegetation-cover changes over the study period. It accepts data in a specific order, or a random order, and is widely used to test the significance of geographical and climatic time-series data [57–59]. These methods were used to determine the total spatial and temporal variation in vegetation cover in Chongqing from 2000–2020. The formula for Theil-Sen slope analysis is as follows:

\[ \text{Slope} = \text{Median} \left( \frac{\text{NDVI}_i - \text{NDVI}_j}{i - j} \right), \forall i < j \]  

(2)

where \( \text{Slope} \) indicates the trend of vegetation-cover change; when \( \text{Slope} > 0 \), the vegetation cover exhibits an increasing trend. Otherwise, it exhibits a decreasing trend. \( i \) and \( j \) indicate different years.

The formula for the Mann–Kendall test is as follows [60]:

\[ S = \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} \text{sgn}(\text{NDVI}_j - \text{NDVI}_i) \]  

(3)

\[ \text{sgn}(\text{NDVI}_j - \text{NDVI}_i) = \begin{cases} +1, & \text{NDVI}_j - \text{NDVI}_i > 0 \\ 0, & \text{NDVI}_j - \text{NDVI}_i = 0 \\ -1, & \text{NDVI}_j - \text{NDVI}_i < 0 \end{cases} \]  

(4)

\[ \text{VAR}(S) = \frac{n(n - 1)(2n + 5) - \sum_{p=1}^{d} t_p (t_p - 1) (2t_p + 5)}{18} \]  

(5)

\[ Z = \begin{cases} \frac{S-1}{\sqrt{\text{VAR}(S)}}, & S > 0 \\ 0, & S = 0 \\ \frac{S+1}{\sqrt{\text{VAR}(S)}}, & S < 0 \end{cases} \]  

(6)

where \( n \) is the time series in this study and \( Z \) reflects the significance of vegetation-cover change, with the time series trend significant at the 0.05 level when \( Z > 1.96 \) or \( Z < -1.96 \) [49].

2.3.4. Pearson Correlation Analysis

Pearson correlation analysis can describe the correlation between two variables [61–63]. In this paper, Pearson correlation coefficients were used to determine the effects of precipitation, temperature, and afforestation area on vegetation-cover changes from 2000–2020. The correlation coefficient \( (R) \) is expressed using the following equation:

\[ R = \frac{\sum_{i=1}^{n}(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i - \bar{x})^2} \sqrt{\sum_{i=1}^{n}(y_i - \bar{y})^2}} \]  

(7)

\( x_i \) indicates vegetation cover data for the \( i \)th year and \( y_i \) indicates the precipitation, temperature, or afforestation area data for the \( i \)th year. If \( R > 0 \), the two factors are positively
correlated; otherwise, they are negatively correlated. Significance tests were also carried out for both factors [39].

2.3.5. Residual Trend Analysis

Residual trend analysis can measure the impact of human activities on changes in vegetation cover [64,65]. There are two reasonable assumptions involved in this type of analysis. The first assumption is that vegetation cover is influenced by a combination of human activities and climate change. The second assumption is that the two main climatic factors, temperature and precipitation, can adequately reflect the effects of climate change on vegetation cover [62,66,67]. Multiple linear regression was used to calculate predicted NDVI values influenced only by climatic factors, with temperature and precipitation—the two main climatic factors affecting vegetation-cover change—being used as independent variables [68,69]. The equations are as follows:

\[ NDVI_c = k_1 P + k_2 T + b \]  
\[ NDVI_H = NDVI_{obs} - NDVI_c \]  
\[ NDVI_H = mt + n \]  

\( P \) and \( T \) are the values of the precipitation and temperature factors, respectively, and \( k_1 \) and \( k_2 \) are the regression coefficients for precipitation and temperature, respectively. \( NDVI_{obs} \) is the remote sensing data value, \( NDVI_c \) is the vegetation cover value influenced by precipitation and temperature only, and \( NDVI_H \) is the residual value influenced by human activities only. The last equation is used to fit the time series and residuals, with \( m > 0 \) indicating that human activities have contributed to the increase in vegetation cover.

2.3.6. Analysis of Relative Roles

We constructed three scenarios to assess the relative contribution of human activities and climatic factors to changes in vegetation cover (Table 1) [70,71]. The relative contributions can be obtained by analyzing the values of \( NDVI_{obs} \), \( NDVI_H \), and \( NDVI_c \) through Theil–Sen slope analyses in combination with Table 1. \( Slope_{c} \), \( Slope_{H} \), and \( Slope_{obs} \) denote the results of Theil–Sen slope analysis performed on \( NDVI_{H} \), \( NDVI_{c} \), and \( NDVI_{obs} \), respectively.

Table 1. Methodology for calculating the relative contribution of different factors to changes in vegetation cover.

| Partition | Scenario | \( Slope_{c} \) | \( Slope_{H} \) | Relative Contribution of Climatic Factors (%) | Relative Contribution of Human Activities (%) | Driving Forces |
|-----------|----------|----------------|----------------|---------------------------------------------|---------------------------------------------|----------------|
| \( > 0 \) | Scenario 1 | >0 | >0 | Slope \( \frac{Slope_{obs}}{Slope_{c}} \) | Slope \( \frac{Slope_{obs}}{Slope_{H}} \) | climatic factors and human activity |
|          | Scenario 2 | >0 | <0 | 100 | 0 | climatic factors |
|          | Scenario 3 | <0 | >0 | 0 | 100 | human activity |
| \( < 0 \) | Scenario 1 | <0 | <0 | Slope \( \frac{Slope_{obs}}{Slope_{c}} \) | Slope \( \frac{Slope_{obs}}{Slope_{H}} \) | climatic factors and human activity |
|          | Scenario 2 | <0 | >0 | 100 | 0 | climatic factors |
|          | Scenario 3 | >0 | <0 | 0 | 100 | human activity |

2.3.7. Complex Network Model

The complex network model identifies land-use types as nodes of a network, with directed edges between nodes representing land-use conversion processes. This model can be used to analyze the overall characteristics of a network system. In areas showing different trends in vegetation-cover changes, different land-use types play different roles. Using Gephi 0.9.2 to construct the complex network model, the land-use characteristics of areas exhibiting different trends in vegetation-cover change can be analyzed in an integrated manner.

(1) Betweenness centrality
Betweenness centrality is the proportion of shortest paths through a node to all shortest paths \[72\]. The greater the betweenness centrality, the greater the role played by the node in the exchange of information in the network, and the more important the node.

\[ Cb(i) = \sum_{j \neq k} g_{jk}(i) / g_{jk} \]  

where \( Cb(i) \) is the value of betweenness centrality, \( g_{jk} \) is the number of shortest paths between nodes \( j \) and \( k \), and \( g_{jk}(i) \) needs to pass through node \( i \) on the basis of \( g_{jk} \).

(2) Average shortest path length

The average shortest path is the path that minimizes the average distance between nodes and is an important indicator of the overall structural characteristics, such as network connectivity \[73,74\]. This paper uses the average shortest path length to measure the overall stability of land-use systems in areas exhibiting different trends in vegetation-cover change.

\[ L = \frac{1}{N(N-1)} \sum_{i \neq j} d_{ij} \]  

where \( d_{ij} \) is the edge between nodes \( i \) and \( j \), and \( N \) is the number of land-use types \[75\].

2.3.8. Hurst Index

The Hurst index is a statistical method for assessing the sustainability of long time series \[65,76,77\]. In this study, we used the Hurst index to predict future trends in vegetation-cover change. The following is the process for generating the Hurst index.

(1) Define the mean of a time series of vegetation cover over the study interval.

\[ \text{NDVI}_{(\tau)} = \frac{1}{\tau} \sum_{t=1}^{\tau} \text{NDVI}_{(t)} \tau = 1, 2, \ldots, n \]  

(2) Calculate the accumulated deviation.

\[ X_{(t,\tau)} = \sum_{t=1}^{\tau} \left( \text{NDVI}_{(t)} - \text{NDVI}_{(\tau)} \right) 1 \leq t \leq \tau \]  

(3) Establish a range sequence.

\[ R_{(\tau)} = \max_{1 \leq t \leq \tau} X_{(t,\tau)} - \min_{1 \leq t \leq \tau} X_{(t,\tau)} \tau = 1, 2, \ldots, n \]  

(4) Establish a standard deviation sequence.

\[ S_{(\tau)} = \left[ \frac{1}{\tau} \sum_{t=1}^{\tau} \left( \text{NDVI}_{(t)} - \text{NDVI}_{(\tau)} \right)^2 \right]^{\frac{1}{2}} \tau = 1, 2, \ldots, n \]  

(5) Establish the equation for calculating the Hurst index.

\[ \frac{R_{(\tau)}}{S_{(\tau)}} = (\tau)^H H \in (0, 1) \]

A value of \( H \) infinitely close to 0.5 indicates that the time series has stochastic characteristics, with little or no sustainability, and the future trend is unrelated to the study period; for \( H < 0.5 \), the time series is anti-sustainable and the future trend is opposite to that in the study period; for \( H > 0.5 \), the time series is sustainable and the future trend is the same as that in the study period.
3. Results

3.1. Spatial and Temporal Variations in Vegetation Cover

As shown in Figure 3, the average vegetation cover in Chongqing increased significantly from 0.759 in 2000 to 0.819 in 2020. The distribution of vegetation cover is shown in Figure A1. As shown in Figure 4, overall, there was a significant trend towards greening, with 87.37% of the area exhibiting greening and a significant increase in vegetation cover in most areas of Chongqing (Table 2). The areas where the vegetation cover was significantly reduced were mainly central urban areas, such as Beibei District.

![Figure 3. Changes in annual vegetation cover in Chongqing.](image3)

![Figure 4. Changes in vegetation cover from 2000–2020.](image4)
Table 2. Area and proportion of different vegetation-cover changes in Chongqing.

| Trend               | Area (km$^2$) | Proportion (%) |
|---------------------|---------------|---------------|
| Significant increase| 52,425        | 63.62         |
| Non-significant increase | 19,569   | 23.75         |
| Non-significant decrease | 7109      | 8.63          |
| Significant decrease | 3301         | 4.01          |

The variation in vegetation cover in Chongqing in different seasons is shown in Figure 5. Greening occurred in 95.76%, 96.35%, 96.01%, and 97.95% of the area in spring, summer, autumn, and winter, respectively, with the overall greening trend being the most pronounced in winter. In spring, the vegetation cover in the northern and southeastern areas of Chongqing exhibited a significant increasing trend, and the areas with significant decreases in vegetation cover were mainly concentrated in the central urban areas, such as Yubei District, Nanan District, and Jiangbei District. The areas that did not exhibit significant decreases were also located in the main urban areas, but they were more extensive than the areas that showed significant decreases, and included areas such as Fuling District and Changshou District. In summer, the vegetation cover in northern and southeastern Chongqing still exhibited significant increases, and the areas with significant decreases were mainly located in the central area, the western area, and the marginal areas of Qianjiang District. The non-significantly increasing areas were scattered throughout Chongqing, and mostly located in the western part of the city. In autumn, vegetation cover increased in most areas, except for the nine central urban areas, such as Beibei District. The northern area, the southeastern area, and the western area experienced an insignificant increase in marginal locations. In winter, the vegetation cover exhibited a significant increasing trend in far more areas of Chongqing than in other seasons. The vegetation cover exhibited a non-significant decreasing trend in areas along the Yangtze River basin, and a significant decreasing trend in the Jiangbei, Nanan, and Yubei districts. The overall vegetation cover exhibited a significant increase, while a few areas in the western and central regions exhibited a non-significant increase.

3.2. Response of Vegetation Cover to Climatic Factors

As temperature and precipitation are the main drivers of climate change [3,78], it is imperative to explore the response of vegetation-cover changes to these two factors. Overall, the areas with significant positive correlations between vegetation cover and temperature and vegetation cover and precipitation were 3607 km$^2$ and 16,624 km$^2$, respectively, indicating that the positive correlation between vegetation cover and precipitation was more significant than that with temperature (Table 3). The two factors had the most areas with a non-significant positive correlation with vegetation cover. In terms of the temperature, the areas with significant positive correlations were mainly located in Hechuan, Tongliang, Dazu, and Rongchang districts, in the western part of Chongqing (Figure 6). The areas with non-significant negative correlations were mainly located in the northern and southeastern parts of Chongqing, while the areas with significant negative correlations were scattered in the northern parts of Chongqing. At higher temperatures, water evaporation is accelerated, which discourages the growth of vegetation; this could explain why vegetation cover is significantly negatively correlated with temperature in some regions [39].
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In terms of the temperature, the areas with significant positive correlations were mainly located in Hechuan,

Table 3. Correlation of vegetation cover with climatic factors.

| Type                        | Precipitation | Temperature |
|-----------------------------|---------------|-------------|
|                             | Area ($\text{km}^2$) | Proportion (%) | Area ($\text{km}^2$) | Proportion (%) |
| Negative correlation ($p < 0.05$) | 1839          | 2.23         | 1319          | 1.60          |
| Negative correlation ($p > 0.05$) | 15986         | 19.40        | 31873         | 38.68         |
| Positive correlation ($p > 0.05$) | 47955         | 58.19        | 45605         | 55.34         |
| Positive correlation ($p < 0.05$) | 16624         | 20.17        | 3607          | 4.38          |

Figure 5. Changes in vegetation cover over the seasons: (a) spring, (b) summer, (c) autumn, and (d) winter.
The distribution of vegetation cover affected by human activities in 2000 and 2020 is shown in Figure A2. In terms of the precipitation, there were few regions that had significant negative correlations, with an area of 1839 km², and were mainly located in the central urban areas, such as Yubei District and Shapingba District. The areas that were not significantly negatively correlated were mainly concentrated in the Chengkou and Wuxi counties at the northern edge of Chongqing city, and in the western part of Chongqing city. The areas with significant positive correlations were mainly concentrated in the central and southern parts of Chongqing, which may be related to the higher precipitation in the southern part of the city [49]. The areas with non-significant positive correlations were larger, with an area of 47,955 km², and were mainly located in Kaizhou District, Yunyang County, and Fengjie County. Higher rainfall contributes to vegetation growth; this could explain why there are fewer areas where vegetation cover and rainfall exhibit a significant negative correlation [39].

3.3. Response of Vegetation Cover to Human Activity

In addition to climatic factors, factors related to human activities, such as the implementation of environmental conservation policies—which include afforestation policies—significantly affect the spatial and temporal changes in vegetation cover. Therefore, it is necessary to investigate the response of vegetation cover to human activity. In this study, the predicted NDVI values were obtained by building a multiple linear regression model based on precipitation and temperature, and the residual values were obtained by subtracting the predicted values from the true values, which can reflect the influence of human activities on vegetation cover. The distribution of vegetation cover affected by human activities in 2000 and 2020 is shown in Figure A3. In this study, the trends of vegetation-cover changes influenced by human activities are divided into four categories, and the effects of human activity on vegetation cover are shown in Figure 7. Overall, vegetation cover exhibits an increasing trend.
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The distribution of vegetation cover affected by human activities in 2000 and 2020 is shown in Figure A3. In this study, the trends of vegetation-cover changes influenced by human activities are divided into four categories, and the effects of human activity on vegetation cover are shown in Figure 7. Overall, vegetation cover exhibits an increasing trend.

Figure 7. Impact of human activities on changes in vegetation cover.

The residual trends with significant increases in vegetation cover were mainly located in the northern and eastern parts of Chongqing, with a total area of 39,176 km² (Table 4). Non-significant increases were mainly found in the central and western regions, with a total area of 29,522 km². Human activities had a positive impact on the vegetation-cover changes in areas that showed an increasing trend. Chongqing has implemented policies such as the Natural Forest Resources Protection Project (NFRP) and the Grain for Green Program (GFGP), whose main objectives are to protect natural forests and to restore woodlands and grasslands according to local conditions, respectively, which can have a positive impact on vegetation-cover changes. These ecological protection policies can explain the increasing trend of vegetation cover in some regions. Yubei District, Shapingba District, Jiulongpo District, Dadukou District, Nanan District, and Jiangbei District, which are located in the central area, exhibited a significant downward trend, while the areas that did not exhibit a significant decline were mainly located in the central and western parts of Chongqing. Human activities had a negative impact on the vegetation-cover changes in these areas, with decreasing trends. The results show that vegetation-cover changes are related to human activities, in addition to climatic factors.
Table 4. Area and proportion of vegetation cover affected by human activities.

| Trend                  | Area (km²) | Proportion (%) |
|------------------------|------------|----------------|
| Significant increase   | 39,176     | 47.54          |
| Non-significant increase| 29,522     | 35.83          |
| Non-significant decrease| 11,532     | 13.99          |
| Significant decrease   | 2174       | 2.64           |

3.4. Relative Contribution of Climate Change and Human Activities to Changes in Vegetation Cover

3.4.1. Analysis of the Spatial Distribution of Driving Forces Affecting Vegetation-Cover Changes

Figure 8 shows the spatial distribution of the drivers of vegetation-cover change. The combined effects of climate change and human activities led to an increase in vegetation cover in 71.95% of the area (Table 5), primarily in the northern and southeastern parts of Chongqing Municipality. The areas with increased vegetation cover due to climate change were distributed in the western and northern fringes of Chongqing, accounting for 4.94% of the total area. The areas with vegetation cover increases due to human activities were distributed in Yunyang County, Fengjie County, Wushan County, and Wuxi County, accounting for 10.74% of the total area. The combined effects of climate change and human activities led to a decrease in vegetation cover in 7.38% of the area, primarily in the central and western regions. The areas with reduced vegetation cover due to climate change were mainly distributed in Yongchuan District, Jiangjin District, and Tongliang District. The areas with reduced vegetation cover due to human activities were mainly distributed in Dianjiang County, Changshou District, and Fuling District, accounting for 4.06% of the total area.

Figure 8. Spatial distribution of drivers of vegetation-cover change in Chongqing from 2000–2020. CV denotes climate variations and HA denotes variations due to human activities.
Table 5. Area and proportion of vegetation-cover changes influenced by different drivers.

| Partition                      | Area (km$^2$) | Proportion (%) |
|--------------------------------|---------------|----------------|
| Areas of increased vegetation cover | 4056          | 4.94           |
| CV                             |               |                |
| Areas of increased vegetation cover | 59,051        | 71.95          |
| CV and HA                      |               |                |
| Areas of decreased vegetation cover | 8814          | 10.74          |
| HA                             |               |                |
| Areas of decreased vegetation cover | 765           | 0.93           |
| CV                             |               |                |
| Areas of decreased vegetation cover | 6055          | 7.38           |
| CV and HA                      |               |                |
| Areas of decreased vegetation cover | 3336          | 4.06           |
| HA                             |               |                |

* CV denotes climate variations and HA denotes variations due to human activities.

3.4.2. Relative Contribution of Drivers in Areas of Decreased Vegetation Cover

This study analyzed the relative contribution of the two drivers to vegetation-cover change based on multiple linear regression and residual analysis. In areas with decreased vegetation cover, climate change and human activities had relative contributions of 29.61% and 70.39%, respectively. As shown in Figure 9b, 75.48% of the vegetation cover reduction areas were mainly caused by human activities (relative contribution > 50%), and were primarily in the western and northwestern parts of Chongqing. Only 24.52% of the areas with decreased vegetation cover were primarily caused by climate change and were mainly found at the western margin (Figure 9a).

![Figure 9. Relative contribution of (a) climate change and (b) human activities on areas of decreased vegetation cover.](image-url)

3.4.3. Relative Contributions of Drivers in Areas with Increased Vegetation Cover

In areas where vegetation cover increased, the average relative contributions of human activities and climate change were 69.14% and 30.86%, respectively. Human activities were the main reason for improvements in vegetation cover over the past two decades. The area of vegetation cover increase mainly caused by human activities accounted for 76.28% of the total area (relative contribution > 50%), and was mainly distributed in the northern and southeastern parts of Chongqing (Figure 10b). The area of vegetation cover increase mainly caused by climate change accounted for 23.72% of the total area, and was mainly distributed in the central and western regions (Figure 10a).
3.4.3. Relative Contributions of Drivers in Areas with Increased Vegetation Cover

In areas where vegetation cover increased, the average relative contributions of human activities and climate change were 69.14% and 30.86%, respectively. Human activities were the main reason for improvements in vegetation cover over the past two decades. The area of vegetation cover increase mainly caused by human activities accounted for 76.28% of the total area (relative contribution > 50%), and was mainly distributed in the northern and southeastern parts of Chongqing (Figure 10b). The area of vegetation cover increase mainly caused by climate change accounted for 23.72% of the total area, and was mainly distributed in the central and western regions (Figure 10a).

3.5. Impact of Afforestation Policies on Changes in Vegetation Cover

Afforestation policies focus on ecological restoration, playing a key role in increasing vegetation cover and preventing soil erosion; thus, they have a positive impact on the regional ecological environment and socio-economic development. The Natural Forest Resources Protection Project (NFRP) began as a pilot project in 1998 and was officially launched in Chongqing in 2000. The Grain for Green Program (GFGP) was piloted in Chongqing in late 1999. China Forestry Statistical Yearbook counted the afforestation area of key ecological projects in forestry, and only NFRP and GFGP were included in the forestry key ecological projects in Chongqing from 2000 to 2016. Although the afforestation area of Stone Desertification Control Project and Yangtze River Basin Key Protection Forest System Project were counted from 2017 to 2019, the afforestation area was much smaller than that of NFRP and GFGP. Therefore, NFRP and GFGP are key ecological projects related to forestry in Chongqing and are the main afforestation policies focused on in this paper.

3.5.1. Analysis of Vegetation-cover Change Based on Complex Network Models

The complex network model can be used to describe the conversion between land-use types. The direction of the directed edge between the nodes represents the conversion direction, and the number on the directed edge represents the conversion weight: the larger the conversion weight, the larger the converted area. The spatial distribution of land use types in different regions in 2000 and 2020 is shown in Figures A4 and A5, and the quantitative status is shown in Tables A1 and A2. As shown in Figure 11, in areas where the vegetation cover exhibited an increasing trend, high weight conversion occurred during the conversion of cropland to forest land, cropland to grassland, and grassland to forest land, while the conversion weight of cropland to construction land was lower than that in areas where the vegetation cover decreased. In regions with decreasing vegetation cover trends, a large amount of cropland was converted to construction land, while there were fewer conversions of other land-use types to forest land and grassland. The GFGP can help restore cropland unsuitable for agricultural cultivation to forest land and grassland, and the NFRP can promote the conversion of other land-use types to forest land. Therefore, areas of increased vegetation cover are the main areas for NFRP and GFGP implementation.
In this study, a complex network model based on betweenness centrality and the average shortest path was used, leading to an understanding of key land-use types and overall land-use system stability for areas with different vegetation-cover change trends. Higher values of betweenness centrality indicate that a given land-use type is more important. As can be seen from Table 6, in areas with significant increases in vegetation cover, woodland and cropland had the highest betweenness centrality values in comparison to other land-use types; therefore, it is assumed that woodland and cropland played a key role in the significant increase in vegetation cover. In areas with no significant increase in vegetation cover, the highest betweenness centrality was found in cropland, followed by grassland and watershed. Consequently, grassland and watershed had a higher betweenness centrality and played a partial role in the increase in vegetation cover. The area contained part of the Three Gorges Dam project inundation zone, so an increase in the size of the watershed occurred, which may partially explain the critical role of water. In areas where vegetation cover was decreasing, the betweenness centrality of both woodland and grassland was 0. Therefore, woodlands and grasslands contribute more to areas where vegetation cover exhibits an increasing trend. This could indicate that ecological conservation policies related to forestry play an important role in areas where vegetation cover has increased.
Table 6. Betweenness centrality of land-use types in regions with different vegetation-cover change trends.

| Land-Use Type     | Significant Increase | Non-Significant Increase | Non-Significant Decrease | Significant Decrease |
|-------------------|----------------------|--------------------------|--------------------------|----------------------|
| Cultivated land   | 1.75                 | 3.0                      | 1.5                      | 0.0                  |
| Forest            | 1.75                 | 0.0                      | 0.0                      | 0.0                  |
| Grassland         | 0.0                  | 1.5                      | 0.0                      | 0.0                  |
| Water area        | 0.25                 | 1.5                      | 1.5                      | 0.0                  |
| Construction land | 0.25                 | 0.0                      | 0.0                      | 0.0                  |
| Unused land       | 0.0                  | 0.0                      | 0.0                      | 0.0                  |

The average shortest path is used to represent the overall land-use system stability, with higher values indicating higher land-use system stability. As can be seen from Table 7, the mean shortest paths in areas with significantly increasing and non-significantly increasing vegetation cover are 1.133 and 1.2, respectively; both values are higher than those with decreasing vegetation cover. Therefore, areas with increasing vegetation cover have higher land-use system stability.

Table 7. Average shortest paths for areas with different vegetation cover trends.

| Vegetation Cover Trends | Average Shortest Path |
|-------------------------|-----------------------|
| Significant increase    | 1.133                 |
| Non-significant increase| 1.2                   |
| Non-significant decrease| 1.12                  |
| Significant decrease    | 1.0                   |

3.5.2. Effect of Afforestation Area on Vegetation Cover

To understand the impact of afforestation on vegetation cover, we used the Pearson correlation method to analyze the correlation between the cumulative afforestation area and vegetation cover. As shown in Table 8, the cumulative afforestation area in Chongqing, from 2000–2019, was 36,924.65 km$^2$. The largest area was afforested during 2015–2019, at 12,462.78 km$^2$, accounting for 33.75% of the cumulative afforestation area. Figure 12 shows a significant correlation between the average annual vegetation cover and the cumulative afforestation area in Chongqing. Two key forestry ecological projects, the NFRP and GFGP, have contributed significantly to increases in the afforestation area, and are the main ecological projects related to afforestation in Chongqing. Due to the availability of data, we accounted for the annual increase in afforestation areas brought about by the two major policies from 2008. As can be seen in Table 9, the contribution of the NFRP to the annual afforestation area was largely higher than that of the GFGP before 2014. However, after 2015, the contribution of the GFGP to the annual afforestation area was higher, and the cumulative afforestation area from 2000–2019 was also higher than that of the NFRP. Therefore, it is clear that the GFGP contributed more to the increase in vegetation cover during the study period.

Table 8. Area and proportion of afforestation in Chongqing in different time periods.

| Period     | Area (km$^2$) | Proportion (%) |
|------------|---------------|----------------|
| 2000–2004  | 8639.68       | 23.40          |
| 2005–2009  | 4572.41       | 12.38          |
| 2010–2014  | 11,249.78     | 30.47          |
| 2015–2019  | 12,462.78     | 33.75          |
3.6. Analysis of Future Vegetation Cover Trends

The spatial distribution of the Hurst index calculated from NDVI data from 2000–2020 is shown in Figure 13. The domain of the Hurst index values ranged from 0.11 to 0.92, and the area of the Hurst index in the range of 0.35–0.50 and 0.50–0.65 was 59% and 22% of the total area, respectively. Generally, we define Hurst index values in the range of 0.35–0.65 as slightly sustainable; therefore, most of Chongqing city lies within the slight sustainability range. The areas within the 0.00–0.25 and 0.75–1.00 values comprised less than 1.5% of the total area. Overall, the area where vegetation-cover change exhibited sustainability (Hurst index > 0.5) was 19,755 km$^2$, accounting for 24% of the total area, and lay mainly in the central districts of Shapingba, Yubei, Jiangbei, Yuzhong, and Nanan, which will exhibit similar vegetation-cover changes in the future as those in the past. The areas showing anti-sustainability (Hurst index < 0.5) of vegetation-cover change were scattered in various

Figure 12. Correlation between cumulative afforestation area and average vegetation cover.

Table 9. Area of afforestation for two key ecological projects related to forestry.

| Year | The Natural Forest Resources Protection Project Afforestation Area (km$^2$) | The Grain for Green Program Afforestation Area (km$^2$) |
|------|-------------------------------------------------|-------------------------------------------------|
| 2008 | 812.42                                          | 200                                             |
| 2009 | 426.67                                          | 366.71                                          |
| 2010 | 600                                             | 303.12                                          |
| 2011 | 326.69                                          | 262.69                                          |
| 2012 | 246.69                                          | 230.02                                          |
| 2013 | 236.68                                          | 243.35                                          |
| 2014 | 70.48                                           | 40.01                                           |
| 2015 | 315.53                                          | 676.02                                          |
| 2016 | 220.01                                          | 656.58                                          |
| 2017 | 226.67                                          | 487.24                                          |
| 2018 | 174.64                                          | 1000                                            |
| 2019 | 156.16                                          | 695.95                                          |
| Cumulative value | 3812.64                                      | 5161.69                                        |
areas of Chongqing, and the future vegetation-cover changes in these areas would be opposite to those in the past.

Figure 13. Spatial distribution of the Hurst index from 2000–2020.

To further analyze the future vegetation-cover changes in Chongqing, this study overlaid the vegetation-cover change trend map with the Hurst index classification results to obtain a spatial distribution map of future vegetation-cover changes (Figure 14). Future changes in vegetation cover were classified according to the Hurst index and trends in vegetation-cover change (Table 10). As shown in Table 11, 72.92% of the future vegetation cover in Chongqing will exhibit a degradation trend, of which 52.70% will show a slight anti-sustainability and improvement trend. An amount of 15.52% of the area showed strong anti-sustainability and improvement, indicating that the vegetation cover in this part of the city had an improvement trend in the past and will degrade in the future due to the influence of human activities and climate change. In contrast, 27.08% of the area exhibited an improvement trend in future vegetation cover, while 18.30% of the area showed slight sustainability and an improving trend. Areas with significantly improved vegetation cover were scattered in the central and western regions, while areas with significant degradation were scattered throughout Chongqing Municipality.
Table 10. Classification of future vegetation-cover change trends.

| Future Vegetation Cover Trends | Hurst Index | Improvement (Slope_{obs} > 0) or Degradation (Slope_{obs} < 0) |
|-------------------------------|-------------|---------------------------------------------------------------|
| Strong sustainability and degradation | 0.65 ≤ H < 1.00 | degradation |
| Slight sustainability and degradation | 0.5 ≤ H < 0.65 | degradation |
| Slight anti-sustainability and degradation | 0.35 ≤ H < 0.5 | degradation |
| Strong anti-sustainability and degradation | 0.00 ≤ H < 0.35 | degradation |
| Strong anti-sustainability and improvement | 0.00 ≤ H < 0.35 | improvement |
| Slight anti-sustainability and improvement | 0.35 ≤ H < 0.5 | improvement |
| Slight sustainability and improvement | 0.5 ≤ H < 0.65 | improvement |
| Strong sustainability and improvement | 0.65 ≤ H < 1.00 | improvement |

Table 11. Area and proportion of different vegetation-cover change trends in the future.

| Future Vegetation Cover Trends | Area (km²) | Proportion (%) |
|-------------------------------|------------|---------------|
| Strong sustainability and degradation | 630 | 0.77% |
| Slight sustainability and degradation | 3227 | 3.93% |
| Slight anti-sustainability and degradation | 5170 | 6.29% |
| Strong anti-sustainability and degradation | 1192 | 1.45% |
| Strong anti-sustainability and improvement | 12,756 | 15.52% |
| Slight anti-sustainability and improvement | 43,311 | 52.70% |
| Slight sustainability and improvement | 15,043 | 18.30% |
| Strong sustainability and improvement | 855 | 1.04% |

4. Discussion

4.1. Afforestation Policies

The results of the study show that the residual trend of vegetation cover showing an increasing trend accounted for 83.37% of the total study area, indicating that human activities, including afforestation, had a positive impact on vegetation-cover change in most areas.
of Chongqing (Table 4). The relative contribution of human activities to vegetation-cover change was 70.39% and 69.14% in areas with decreasing and increasing vegetation cover, respectively; therefore, it is clear that human activities have an important contribution to vegetation-cover changes. The Chinese government is placing an increasing emphasis on environmental protection through the implementation of a number of forestry-related ecological protection policies [79]. Forestry ecological projects, including NFRP and GFGP, had a positive impact on vegetation-cover change in Chongqing (Figure 12). As can be seen from Table 6, forest land and grassland contributed more to the areas with an increasing trend of vegetation cover, which also indicates that forestry-related ecological policies play an important role in improving vegetation cover. These ecological protection policies prevent soil erosion and promote ecological improvements. Afforestation improves vegetation cover in its natural state and positively affects crop yields indirectly by preventing soil erosion and impacting the climate [80,81].

However, the correlation between afforestation area and vegetation-cover change varied somewhat in different provinces, and there was a smaller correlation between vegetation-cover change and afforestation area increase in some provinces [71]. The reasons for not achieving the expected effect could be human factors such as different afforestation densities, inappropriate afforestation methods, or the incorrect selection of tree species. A high-density silvicultural strategy may make natural precipitation insufficient for vegetation growth, and could also lead to a decline in soil moisture [71]. Local conditions need to be taken into account when afforestation is conducted. If deep-rooted trees are selected where the water table is low, this can lead to degradation of the grassland due to a lack of access to sufficient water [82].

4.2. Urban Development and Improvement of Vegetation Cover

In addition to the positive impact of human activities on vegetation-cover changes in some areas, they have also contributed to the degradation of vegetation cover. As shown in Figure 11, in areas where vegetation cover was decreasing, there was a large amount of conversion of cropland to building land and less conversion of other land-use types to woodland and grassland. These areas, with large increases in construction land, are mainly located in fast-growing areas. With accelerated urbanization, it is inevitable that construction land will increase; however, this decreases vegetation cover in some areas [83]. The government should pay more attention to the construction of urban parks and green spaces, and implement stronger initiatives to make the concept of sponge and ecological cities more popular, which can help improve the vegetation cover of human settlements [49].

In the future, 72.92% of the vegetation cover in Chongqing will be at risk of degradation (Table 11), which may be due to the accelerated urbanization process leading to the replacement of agricultural land, forest land, and grassland with construction land. Some central urban areas have an improving trend of vegetation cover, which may be due to the government’s gradual emphasis on the construction of ecological cities and sponge cities [84]. Different regions have different climatic conditions and environmental protection measures; therefore, vegetation-cover changes are also diverse [85]. Only a few regions had vegetation-cover changes influenced by climatic factors or human activities alone, and the majority of regions had vegetation-cover changes being influenced by the combined effect of climatic factors and human activity (Table 5). The results of betweenness centrality calculations showed that woodland and grassland played a key role in areas with increasing vegetation cover trends (Table 6), and the conversion weights of cropland to woodland and cropland to grassland were higher (Figure 11); therefore, it is clear that the NFRP and GFGP played an important role in areas with significantly increasing vegetation cover trends. Although the government has adopted some ecological protection policies regarding forestry, there is still a risk of degradation of vegetation cover in more than half of the area of Chongqing in the future (Table 11). This indicates that the implementation of current forestry-related ecological policies is still insufficient, and the implementation
Methods should be improved. Therefore, suitable afforestation methods and tree species should be selected according to local climate and soil conditions, and future policies should focus on parks, green belts, and green roofs [30]. In addition, the afforestation policy needs to strengthen the management and maintenance of trees at a later stage in order to give full play to the policy, so the government needs to invest in the policy continuously, consider its socio-economic benefits and make a detailed afforestation plan. At the same time, it should not only avoid affecting the growth of the original trees in the afforestation process, but also restore natural forests as much as possible [30]. More attention should be paid to the positive impacts of human activities, identifying the shortcomings of previous policies and improving the said policies, which can help to improve vegetation cover while promoting urban development.

5. Conclusions

In this study, we analyzed the spatial and temporal changes of vegetation cover in Chongqing city over four seasons, the drivers of vegetation-cover changes and their relative contributions, and analyzed forestry-related ecological policies using complex network models. The results of Theil–Sen slope analysis and Mann–Kendall tests showed that 87.37% of the areas exhibited greening. The areas with significantly decreased vegetation were mainly the central urban areas, such as Beibei District, and the overall greening trend was most obvious in winter. The positive correlation between vegetation cover and precipitation was more significant in Chongqing than that with temperature. In terms of the temperature, the areas with significant positive correlations were mainly located in the Hechuan, Tongliang, Dazu, and Rongchang districts in the western part of Chongqing. In terms of precipitation, the areas with significant positive correlations were mainly concentrated in the central and southern parts of Chongqing, which could be related to the higher precipitation in the southern part of the city [49]. In regions with decreasing vegetation cover, climate change and human activities had relative contributions of 29.61% and 70.39%, respectively. In regions with increased vegetation cover, the average relative contributions of human activities and climate change were 69.14% and 30.86%, respectively. Therefore, human activities are clearly the dominant factor affecting the increase or decrease in vegetation cover in Chongqing. Woodland and grassland were the more critical land-use types in regions with significantly increased vegetation cover, and these regions had higher land-use system stability, indicating that NFRP and GFGP played an important role in regions with significantly increased vegetation cover. The average annual vegetation cover and cumulative afforestation area are significantly correlated, and 72.92% of the future vegetation cover in Chongqing will exhibit a degradation trend, which necessitates increased attention toward the protection of vegetation and the improvement of conventional policies.

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Appendix A

Figure A1. Cont.
Figure A1. The distribution of vegetation cover. (a) 2000, (b) 2020, (c) Spring of 2000, (d) Spring of 2020, (e) Summer of 2000, (f) Summer of 2020, (g) Autumn of 2000, (h) Autumn of 2020, (i) Winter of 2000, (j) Winter of 2020.

Figure A2. Spatial distribution of annual average precipitation in Chongqing from 2000 to 2020.
Figure A3. Distribution of vegetation cover under the influence of human activities. (a) 2000, (b) 2020.

Table A1. Quantitative status of land use types in 2000 in different regions.

| Vegetation Cover Trends | Cultivated Land | Forest | Grassland | Water Area | Construction Land | Unused Land |
|-------------------------|-----------------|--------|-----------|------------|------------------|-------------|
| Significant increase    | 19,881          | 23,184 | 8736      | 369        | 244              | 11          |
| Non-significant increase| 11,120          | 5576   | 2407      | 318        | 146              | 2           |
| Non-significant decrease| 5124            | 1145   | 550       | 173        | 115              | 2           |
| Significant decrease    | 2567            | 440    | 135       | 67         | 92               | 0           |
| Total                   | 38,692          | 30,345 | 11,828    | 927        | 597              | 15          |

Table A2. Quantitative status of land use types in 2020 in different regions.

| Vegetation Cover Trends | Cultivated Land | Forest | Grassland | Water Area | Construction Land | Unused Land |
|-------------------------|-----------------|--------|-----------|------------|------------------|-------------|
| Significant increase    | 19,897          | 25,610 | 5927      | 490        | 454              | 7           |
| Non-significant increase| 11,035          | 6328   | 1339      | 477        | 371              | 4           |
| Non-significant decrease| 4879            | 1208   | 271       | 248        | 496              | 0           |
| Significant decrease    | 1660            | 388    | 55        | 94         | 1077             | 1           |
| Total                   | 37,471          | 33,534 | 7592      | 1309       | 2398             | 12          |
Figure A4. Spatial distribution of land use types in different regions in 2000: (a) significant decrease, (b) non-significant decrease, (c) non-significant increase, and (d) significant increase.
Figure A5. Spatial distribution of land use types in different regions in 2020: (a) significant decrease, (b) non-significant decrease, (c) non-significant increase, and (d) significant increase.

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