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Changes in the Vegetation NPP of Mainland China under the Combined Actions of Climatic-Socioeconomic Factors

Yifeng Liu [1,†], Mei Xu [1,†], Bing Guo [1,*], Guang Yang [2,*], Jialin Li [1] and Yang Yu [1]

1 School of Civil Engineering and Geomatics, Shandong University of Technology, Zibo 255000, China; 21407010765@stumail.sdut.edu.cn (Y.L.); 22407010008@stumail.sdut.edu.cn (M.X.); 21507020776@stumail.sdut.edu.cn (J.L.); 21507020798@stumail.sdut.edu.cn (Y.Y.)
2 Research Institute of Aerospace Information, Chinese Academy of Sciences, Beijing 100101, China
* Correspondence: guobing@sdutedu.cn (B.G.); yangguang@radi.ac.cn (G.Y.); Tel.: +86-18766965987 (B.G.); +86-18510586581 (G.Y.)
† These authors contributed equally to this work.

Abstract: Under the combined impact of climatic, socioeconomic, and environmental factors, the vegetation NPP change process and its responses to drive factors in the sub-regions of Mainland China are not clear. This study analyzes the changing pattern of vegetation NPP in China from 2000 to 2022 from the perspective of zoning and clarifies its response mechanism to climate-human interaction based on the gravity center model, third-order partial correlation coefficient and geographical detector. The results showed that: (1) There was an overall decreasing trend of vegetation NPP in China from the southeast to the northwest; (2) The vegetation NPP gravity center in Northeast, Northwest, and North China migrated southwards, while that of Southwest, Central South, and East China showed northward migration.;(3) Human activities played a dominant role in zones with increasing vegetation NPP from 2000 to 2010, while climate change greatly contributed to the increase in vegetation NPP during 2011–2022; (4) Human activities, such as deforestation and overgrazing, in Northeast and North China should be reduced to prevent vegetation ecosystem degradation, and the negative impact of human activities should be reduced to maintain the growth of vegetation NPP. This study was conducted to support decision-making for the precise restoration of ecosystems.

Keywords: geographic demarcation; spatio-temporal variations; driving mechanisms; dominant factors; geographical detector

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1. Introduction

Net Primary Productivity (NPP) refers to the total amount of organic matter accumulated by green plants per unit area per unit time [1]. Vegetation plays a major role in terrestrial ecosystems, which can better indicate the changes in regional ecological environments. To achieve the dual carbon goals, it is particularly important to clarify the spatial and temporal evolution patterns of vegetation NPP and its response mechanism to climate–human impacts [2].

Recently, research on vegetation NPP has been further conducted. Many scholars have conducted a series of studies on the estimation and analysis of vegetation NPP based on MODIS data [3,4]. Running et al. [5] estimated NPP by considering the difference between Gross Primary Productivity (GPP) and respiration and solving important ecological problems on time and space scales. Potter et al. [6] established a Carnegie–Ames–Stanford Approach (CASA) model to calculate vegetation NPP, aiming to control the seasonal production of terrestrial ecosystems and soil microbial respiration patterns associated with global climate and soil. Field et al. [7] proposed a simple modeling method for global NPP, which combines ecological principles with satellite data to obtain global estimates with an operational monitoring resolution. Mowll et al. [8] pointed out that precipitation played an important role in affecting vegetation NPP. Domestic scholars have conducted many studies on the influencing factors and driving mechanisms of vegetation NPP, such as spatio-temporal change patterns, dominant factors, and driving mechanisms, in different sub-regions of China [9–13]. Relevant studies have shown there is an increasing trend of vegetation in China, and the driving mechanisms of changes in NPP are different in different study areas [14–17].

Previous studies on vegetation NPP in China mainly focused on ecologically fragile areas. For example, Zhu et al. [18] applied the CASA model to analyze the change patterns of vegetation NPP in Inner Mongolia. Wang et al. [19] used the Hurst index to analyze NPP in the Qinling–Daba Mountains during 2000–2015. Yang et al. [20] analyzed the change patterns of vegetation NPP of Qinghai–Tibet Plateau utilizing a gravity center model [21]. Due to the vast territory of China, scholars have conducted many studies on different regions. For example, Xu et al. [22] investigated the evolution process and the influencing factors of different types of vegetation NPP in Southwest China. Li et al. [23] explored the change process of vegetation NPP in the Yangtze River Basin and its relationships with topographic factors. Based on the CASA model, Mao et al. [24] found that climate and land use are important factors affecting the change patterns of vegetation in Northeast China. Liu et al. [25] found that the NPP of vegetation in the Qinghai–Tibet Plateau is significantly positively correlated with temperature and precipitation.

The aims of this study are as follows: (1) To reveal the spatio-temporal evolution patterns of vegetation NPP and its differences in different sub-regions; (2) to systematically determine and clarify the differences in the dominant factors in different sub-regions from the perspective of partition; and (3) to explore the changes in the dominant factors during different historical periods in the same sub-region.

2. Materials and Methods

2.1. Study Area

China is located in the eastern part of Asia, east to the junction of Heilongjiang and the Ussuri (135°2′30″ E), west to the Pamirs (73°29′59.79″ E), south to the Cape Zengmuansha at the southern tip of the Nansha Archipelago (4°15′00″ N), north to the center line of the main channel of Heilongjiang (53°33′ N), with a total area of 9.6 million km^2 (Figure 1). Its terrain decreases from west to east, showing a three-stage ladder-like distribution. China has five types of territories based on relief: plateau, mountain, plain, hill, and basin. Due to its vast land area as well as its large latitude and longitude span, it has formed a variety of temperature and precipitation combinations, forming a complex and diverse climate [22]. There are five climate types in China, which include temperate monsoon, temperate continental, and alpine plateau climates. Yang et al. [26] studied the difference in plateau climate change in Tibet. Due to the large span of the north–south latitude, the north–south spatial heterogeneity of temperature is obvious [23]. There are a variety of vegetation types, which mainly include grasslands, tropical rainforests, and coniferous forests. The soil types (WRB) are complex and diverse and include 15 soil types, such as latosol, latosolic red, and reddish-yellow soils; their distribution varies based on geographical location and terrain height [27].

2.2. Data Source and Preprocessing

NPPs that were derived from the MODIS17A3H dataset were available at https://ladsweb.nascom.nasa.gov/ (accessed on 21 January 2023), with temporal and spatial resolution resolutions of 1 year and 500 m. The MRT (MODIS Reprojection Tool) tool was utilized to reproject and format the vegetation NPP data. The climate data came from the China Meteorological Data Network (http://data.cma.cn/ (accessed on 24 January 2023)), which included daily precipitation, daily average temperature, accumulated temperature (sum of temperatures greater than 10 °C), and sunshine data. Because kriging interpolation may cause interpolation errors compared with traditional methods, the difference result is more accurate. These datasets were interpolated into 1 km grids using ArcGIS 10.7 (Environmental Systems Research Institute, Inc., Redlands, CA, USA). Land use, socioeconomic (population density and GDP), and geographic partition data were retrieved from http://www.resdc.cn/ (accessed on 21 January 2023). The elevation and slope data were extracted from SRTM 90 m, which was downloaded at http://www.Gscloud.cn (accessed on 23 January 2023). Based on the Arcgis10.7 Clip tool for cutting, the abnormal values for the vegetation NPP data were removed, resampled to 1 km, and projected to a Krasovskii projection. The related driving factors and references are shown in Table 1. The soil distribution map, temperature and precipitation distribution map selected by driving factors are shown in Figures 2 and 3.

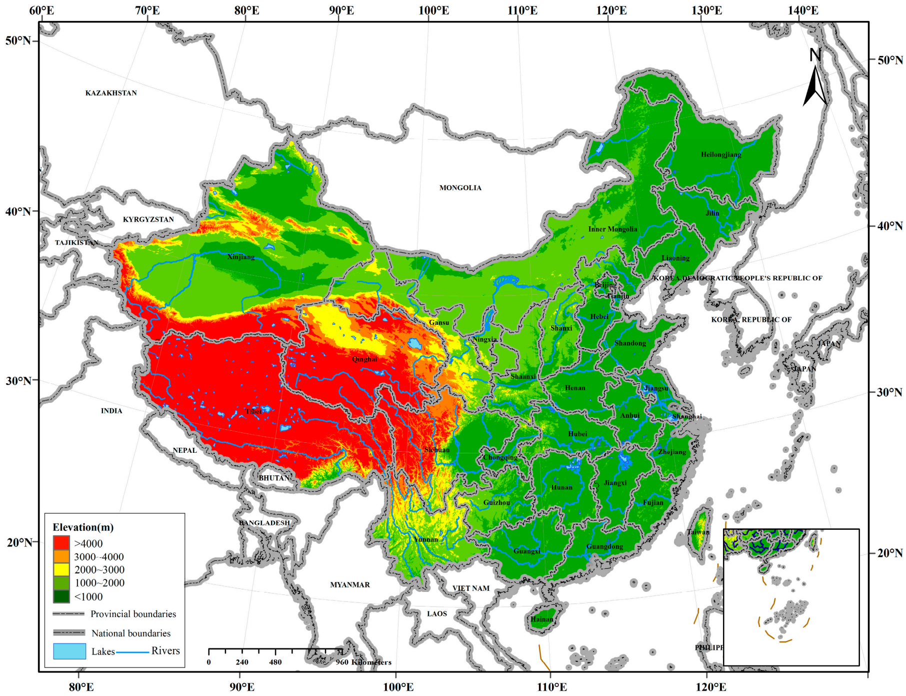


Figure 1. The location overview and elevation distribution map of the study area.

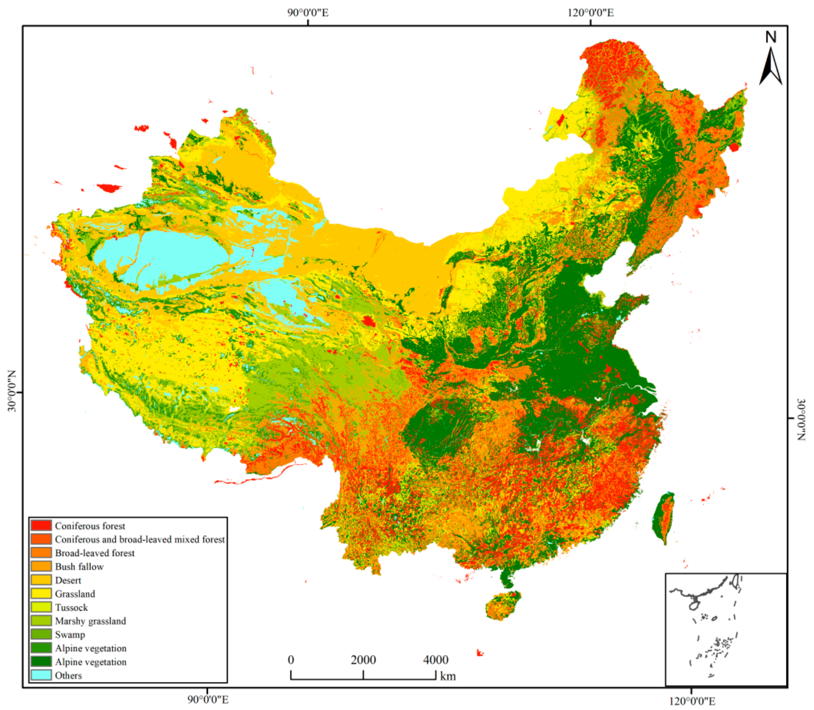
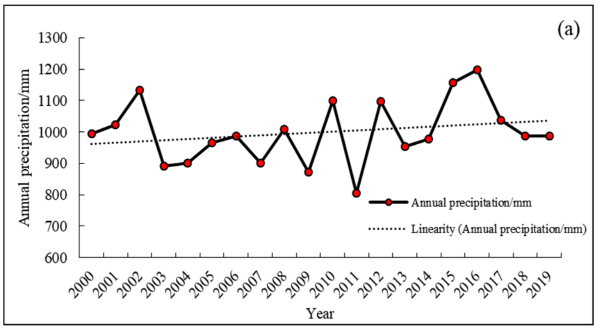


Figure 2. Soil distribution map of the study area.



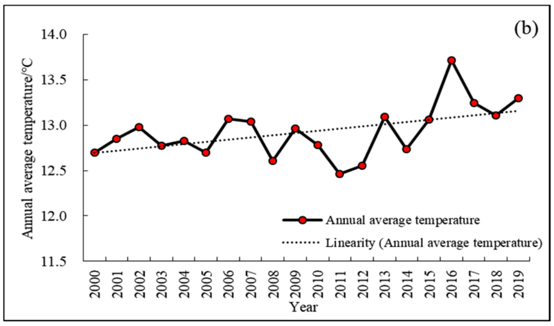


Figure 3. Driving factor line chart. (**a**) Annual precipitation; (**b**) Annual average temperature.

2.3. Methods

Most of the research is based on one partition, and few studies are based on different partitions. This study focuses on these differences, which are of great significance to protecting ecosystems according to local conditions. In addition, against the backdrop of global climate change, the dominant factors in the change process of vegetation NPP have also changed. It is not clear how the evolution mechanisms of vegetation NPP varied across different periods and ecological sub-regions. The related research is mostly based on the driving mechanisms of temperature, precipitation, population, and other factors [24,25,28,29]. Based on the research status, most relevant research has selected these data; in the size of the influence of the driving factors, these factors can well explain the reasons for the change. A series of ecological and environmental problems caused by climate change, such as air pollution and dust storms, are not only troubled. People's lives have also had a negative impact on industrial production, which has hindered the sustainable development of the social economy to a certain extent. Therefore, it is of scientific significance to understand and understand the impact of climate change on vegetation. Therefore, this study selects two climatic factors (temperature and precipitation), two social factors (population density and Gross Domestic Product), and two geographical factors (altitude and slope).

Moreover, previous studies mostly applied second-order partial correlation to explore the effects of different climatic factors on vegetation NPP but ignored the comprehensive and interactive effects of regional multi-type climatic factors. In the past, partial correlation analysis was mostly based on single factor and double factors. In this paper, third-order partial correlation analysis is used as an innovation point, which allows for comprehensively considering the complex effects of three factors on the evolution of vegetation, thereby more truly reflecting ecological processes.

Geodetectors detect the spatial stratification heterogeneity of elements and reveal the driving forces behind them [30], thus making it advantageous for exploring driving mechanisms across different partitions. In this study, we utilized a Geodetector, third-order partial correlation analysis, and a gravity center model to analyze the change process of vegetation NPP in China from the perspective of partitions. The relative role of climate–human interactions during different historical periods was quantitatively distinguished, and the dominant factors of changes in vegetation NPP across different sub-regions and historical periods were revealed. The effects of global change on Chinese vegetation NPP response mechanisms were clarified, which provides support for important decisions regarding the restoration of regional vegetation ecosystems.

The process was mainly divided into three parts: The first part was data preprocessing. The NPP, climate, land (land use, soil type), and socioeconomic (GDP, population density) datasets were preprocessed via kriging interpolation (Co-Kriging), re-projection, and clipping. The second part was the analysis of the spatio-temporal change process. Spatial distribution analysis was carried out from the perspective of mean distribution, different levels of vegetation NPP transfer scenarios, and mean comparative analysis. The analysis of temporal evolution was conducted from the perspective of gravity center migration. The third part was the analysis of the driving mechanisms. The driving factors were explored using a geographic detector. A flow chart of this study is presented in Figure 4.

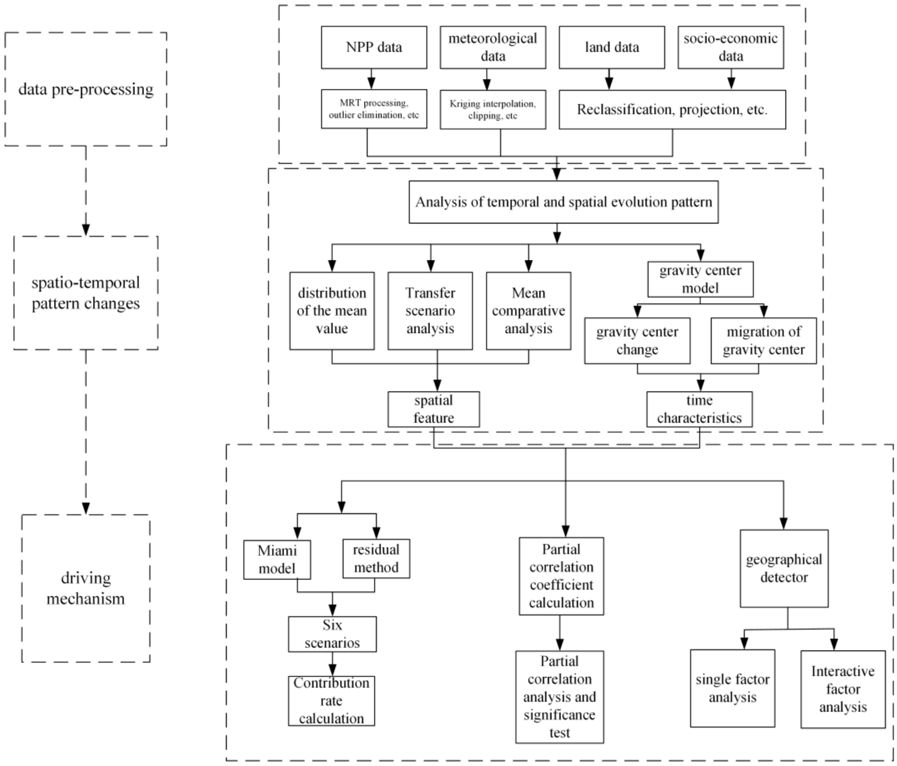


Figure 4. Flow chart of the research method.

2.3.1. Gravity Center Model

In physics, the gravity center refers to a point in a certain space where forces in all directions reach phase equilibrium [31]. Two common barycenter models are the quality gravity center model and the ecological gravity center model. The gravity mass center model is mainly used to describe the mass distribution, while the ecological gravity center model is suitable for describing the spatial distribution of biological communities or ecosystems. In addition, the gravity center model has also been widely applied in life, land use, and other fields. The migration trajectory and direction of the gravity center can directly indicate the change unevenness and the bias of certain phenomena from the perspective of spatial distribution [15,18,26]. Moreover, as typical geophysical and ecological indicators, there were obvious differences in change patterns for vegetation NPP across different periods and sub-regions. However, traditional statistical methods cannot reveal the laws governing changes in temporal and spatial distribution on a large scale [16]. Meanwhile, the migration distance and direction of vegetation NPP gravity center can indicate the increments and growth rate of vegetation NPP in different parts within the study region. The gravity center model can be applied to investigate the variation characteristics of vegetation NPP. The center of gravity model [32] is a mature tool in ArcGIS software with the following formulae:

$$\overline{x} = \frac{\sum_{i=1}^{n} z_i x_i}{\sum_{i=1}^{n} z_i} \tag{1}$$

$$\overline{y} = \frac{\sum_{i=1}^{n} z_i y_i}{\sum_{i=1}^{n} z_i} \tag{2}$$

where $(\overline{x}, \overline{y})$ is the barycenter coordinates, z_i is the attribute value of the i-th plane space element, and (x_i, y_i) is the attribute value of the i-th plane space element.

2.3.2. Third-Order Partial Correlation Coefficient and Significance Test

A correlation coefficient represents the degree of correlation between different elements [33]. The Pearson correlation coefficient was applied to analyze the correlation between vegetation NPP and typical climatic factors and their significance level. Because a first-order partial correlation coefficient can only control one variable, a high-order partial correlation coefficient can reflect the correlations between vegetation NPP and multiple variables. Therefore, this study utilized a third-order partial correlation coefficient to explore the correlations between climate variables and vegetation NPP at the $p < 0.05$ and $p < 0.01$ confidence levels. The formula can be expressed as follows:

$$r_{x,y} = \frac{\sum_{i=1}^{n}(x_i - \overline{x})(y_i - \overline{y})}{\sqrt{\sum_{i=1}^{n}(x_i - \overline{x})^2 \sum_{i=1}^{n}(y_i - \overline{y})^2}} \tag{3}$$

In the formula, $r_{x,y}$ denotes the correlation coefficient (r_{xy_1}, r_{xy_2}, and $r_{y_1y_2}$ are similar) between variables x and y, where a positive value denotes a positive correlation; conversely, x_i and y_i represent the values of the two variables in year i. r_{xy_1,y_2} represents the partial correlation coefficient of x and y_1 in the case of the control variable y_2.

When controlling multiple variables, there are high-order partial correlation coefficients. The formula can be expressed as follows:

$$r_{xy,y_1y_2\cdots y_g} = \frac{r_{xy,y_1y_2\cdots y_{g-1}} - r_{xy_g,y_1y_2\cdots y_{g-1}} r_{yy_g,y_1y_2\cdots y_{g-1}}}{\sqrt{1 - r^2_{xy_g,y_1y_2\cdots y_{g-1}}}\sqrt{1 - r^2_{yy_g,y_1y_2\cdots y_{g-1}}}} \tag{4}$$

2.3.3. Climate–Human Interaction Distinction

The Miami model proposed by H. Lieth [34] is a widely used model to calculate potential vegetation NPP, and it can be expressed as follows:

$$\mathrm{NPP}_c = \min\{(1 + \frac{3000}{\exp(1.315 - 0.119\mathrm{T})}), 3000[1 - \exp(-0.000664\mathrm{P})]\} \tag{5}$$

In the formula, $\mathrm{NPP_c}$ refers to potential NPP ($\mathrm{gC{\cdot}m^{-2}{\cdot}a^{-1}}$); T refers to the average annual temperature (°C); and P refers to annual precipitation (mm).

Vegetation NPP is always influenced by the combined actions of climate–human activities. The residual method has been widely used to separate human-affected NPP from actual NPP [35]. Based on the residual method, NPP affected by human activities was calculated. Meanwhile, the change slope of the potential NPP was calculated to distinguish climate–human interactions according to the positive and negative slopes. This can be expressed as follows:

$$\mathrm{NPP_h} = \mathrm{NPP}_a - \mathrm{NPP}_c \tag{6}$$

In the formula, $\mathrm{NPP_h}$ is the human-influenced NPP, NPP_a is the actual NPP, and NPP_c is the potential NPP. If $\mathrm{NPP}_h < 0$, this indicates that human activities inhibit the increase in NPP. If $\mathrm{NPP}_h > 0$, this indicates that human activities promote an increase in NPP.

The formula to calculate the variation in vegetation NPP is as follows [36]:

$$\Delta\mathrm{NPP} = (n - 1) \times K_{\mathrm{slope}} \tag{7}$$

where n represents the study time scale, and K_{slope} is the change slope of NPP.

Based on the slope of NPP_a, NPP_c, and NPP_h, six scenarios were established to assess the relative contributions of climate-human to NPP change, as shown in Table 2:

Table 1. Different types of index references and contributions.

Index	Factor	References
Climate	Annual precipitation, average temperature, accumulated temperature, and sunshine	[8,9,25,30,32,36]
Terrain	Slope and altitude	
Social development	Population density and GDP	

Table 2. Six scenarios involving the contribution of human–climate interactions to the change in vegetation NPP.

NPP_a Status	Scenario	K_c	K_h	Climate Change Contribution Ratio	Human Activity Contribution Ratio
Increased NPP_a ($K_a > 0$)	Scenario 1	$K_c > 0$	$K_h < 0$	100	0
	Scenario 2	$K_c < 0$	$K_h > 0$	0	100
	Scenario 3	$K_c > 0$	$K_h > 0$	$\frac{\lvert\Delta NPP_c\rvert}{\lvert\Delta NPP_c\rvert+\lvert\Delta NPP_h\rvert}$	$\frac{\lvert\Delta NPP_h\rvert}{\lvert\Delta NPP_c\rvert+\lvert\Delta NPP_h\rvert}$
Reduced NPP_a ($K_a < 0$)	Scenario 4	$K_c < 0$	$K_h > 0$	100	0
	Scenario 5	$K_c > 0$	$K_h < 0$	0	100
	Scenario 6	$K_c < 0$	$K_h < 0$	$\frac{\lvert\Delta NPP_c\rvert}{\lvert\Delta NPP_c\rvert+\lvert\Delta NPP_h\rvert}$	$\frac{\lvert\Delta NPP_h\rvert}{\lvert\Delta NPP_c\rvert+\lvert\Delta NPP_h\rvert}$

In Table 2, K_i represents the slope of NPP_i, where i = a, b, h.

2.3.4. Geodetector

The Geodetector model can determine a factor's contribution rate to vegetation NPP, which is measured by its q-value [37]. The greater the value is, the greater the impact of this factor on NPP is, and vice versa. In this study, temperature, precipitation, population density, GDP, altitude, slope, land use, and soil type were selected, and the q-values of different factors were calculated via the Geodetector model to reveal the influences of different factors on vegetation NPP [28].

$$q = 1 - \frac{\sum_{h=1}^{L} N_h {\sigma_h}^2}{N\sigma^2} = 1 - \frac{SSW}{SST} \tag{8}$$

$$SSW = \sum_{h=1}^{L} N_h {\sigma_h}^2 \tag{9}$$

$$SST = N\sigma^2 \tag{10}$$

In the formula, h = 1, ..., L represents the classification of variable Y or factor X; N_h and N are the layer h and the number of pixels units in the whole region; σ_h the variance in the Y value produces the class h, which is the variance in the Y value of the whole region; SSW and SST are the sum of intra-layer variance and the total variance in the whole region, respectively.

2.3.5. Uncertainty Estimation Approaches

Uncertainty means that the potential and possible results of things cannot or cannot make full use of reasonable and known probability distribution to objectively analyze and characterize, and cannot subjectively analyze and estimate the results. The uncertainty of water resources caused by climate change is difficult to estimate and analyze based on the known probability distribution or subjectively. Therefore, quantitative estimation of the uncertainty of water resources caused by climate change from various aspects can help to understand the uncertainty of water resources.

3. Results

3.1. Spatial Distribution Characteristics of Vegetation NPP

The mean vegetation NPP during 2000–2022 was calculated to analyze its spatial distribution. Figure 5 showed that vegetation NPP in China ranged from 0 to 1933 $gC{\cdot}m^{-2}{\cdot}a^{-1}$. By using ArcGIS 10.7, the vegetation NPP was divided into five grades: level I (<200 $gC{\cdot}m^{-2}{\cdot}a^{-1}$), level II (200–400 $gC{\cdot}m^{-2}{\cdot}a^{-1}$), level III (400–600 $gC{\cdot}m^{-2}{\cdot}a^{-1}$), level IV (600–800 $gC{\cdot}m^{-2}{\cdot}a^{-1}$), and level V (>800 $gC{\cdot}m^{-2}{\cdot}a^{-1}$, as shown in Appendix A, Figure A1). The level V region accounted for the smallest proportion (only 12.54%), which was mostly located in the southern parts, including Guangdong Province, Guangxi, and Yunnan Province. The level IV region accounted for 13%, being mostly located in the central and southern regions, including Guizhou Province and Zhejiang Province. The level III region accounted for 25%, which was mostly located in the central parts, including Shaanxi Province and Anhui Province. The level II region accounted for 25.94%, being distributed in northeast Tibet. The level I region accounted for 25.00%, mainly distributed in the central and western regions, including the foothills of the Tianshan Mountains and Qinghai Province. Overall, the mean vegetation NPP gradually increased from north to south and from west to east.

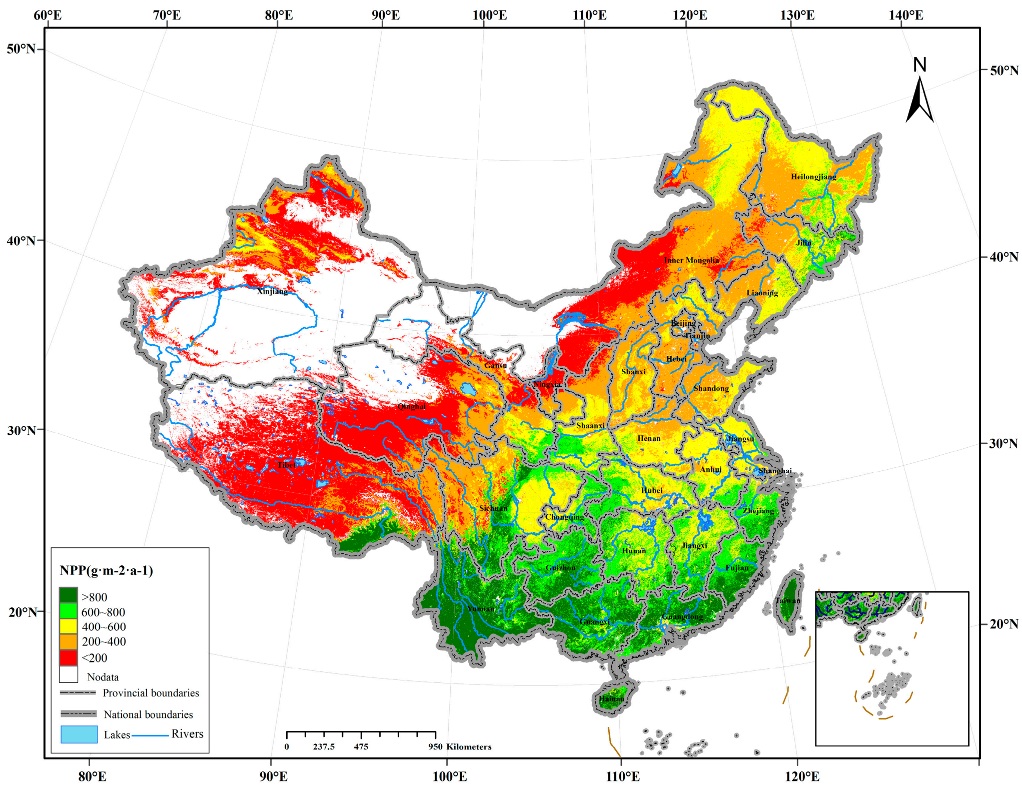


Figure 5. Annual average vegetation NPP in China over the last 23 years.

3.2. Spatial Distribution of Vegetation NPP

To reveal the changes in the different levels of vegetation NPP across different periods, we divided this study into two periods: 2000–2010 and 2011–2022, as shown in Appendix A Figure A2 and FigureA3.

Appendix A Figure A2a and FigureA3a showed that from 2000 to 2010, zones with levels II and III accounted for the largest proportion at 36.56%, which were mainly distributed across the Weihe Plain, Lesser Khingan, southern Henan, and northern Anhui. Secondly, zones with level I converted to zones with level II accounted for 28.06%, mostly concentrated in eastern Inner Mongolia, northern Shaanxi, and southern Qinghai Province. Areas comprising moderate to severe lushness accounted for 15.41%, being mainly distributed in southern Shaanxi, western Hunan, and southern Guangxi. During 2000–2010, zones with levels I and II to zones with levels III, IV, and V had the largest area, indicating that vegetation NPP showed an overall increasing trend.

Appendix A Figure A2b and FigureA3b showed that from 2011 to 2022, in the area where the vegetation NPP level changes, the area transferred from zones with level II to zones with level III accounted for the largest proportion, comprising 34.90%, which was mainly distributed in the Changbai Mountains, Shanxi Province, and western Shandong. The area transferred from zones with level III to zones with level IV accounted for 20.42%, mostly distributed in the Sichuan Basin and the Liaodong Peninsula. The area transferred from zones with level IV to zones with level V accounted for 16.45%, being mostly located in the western part of Guizhou, the central part of Hubei, and the junction of Heilongjiang and eastern Jilin. During 2011–2022, the area of zones with level II to zones with levels III, IV, and V accounted for the largest proportion, indicating that the overall NPP of vegetation showed an increasing trend. Overall, the vegetation NPP showed an increasing trend during 2000–2022.

Appendix A Figure A4 and FigureA5 showed that from 2000 to 2010, the average NPP of vegetation in China ranged from 0 to 1959 gC·m^{-2}·a^{-1}. The area proportion of level I was the largest, comprising 40.5%, which was mostly concentrated in the Qinghai–Tibet Plateau, Inner Mongolia, and other regions. Level V zones accounted for 3.2%, being mainly distributed in southern China, such as southern Fujian Province and the Guangxi Zhuang Autonomous Region. The area proportion of level III zones was 21.6%, being mostly concentrated in central and southern China, such as the Sichuan Basin and Hunan Province. Appendix A Figure A4 shows that the average annual NPP of vegetation in China from 2011 to 2022 had a similar trend to the average NPP of vegetation from 2000 to 2010. The difference is that the proportion of level I and level II zones decreased, and the proportion of level III zones and above had increased. When combined with our quantitative analysis in Appendix A Figure A5, in 2000–2010 and 2011–2022, we found that level I zones accounted for 40.5% and 38.4%, respectively, and the level V zones accounted for 3.2% and 3.6%, respectively.

3.3. Gravity Center Migration of Vegetation NPP

In order to explore the discreteness and bias of vegetation NPP distribution in the study area [38], the gravity center model was utilized to analyze the migration trend of vegetation NPP gravity center from 2000 to 2022 (Figure 6). In the polar coordinate system, the distance (polar diameter) and deflection angle (polar angle) of the gravity center of NPP from 2000 to 2022 were calculated to reflect its dynamic migration (Table 3).

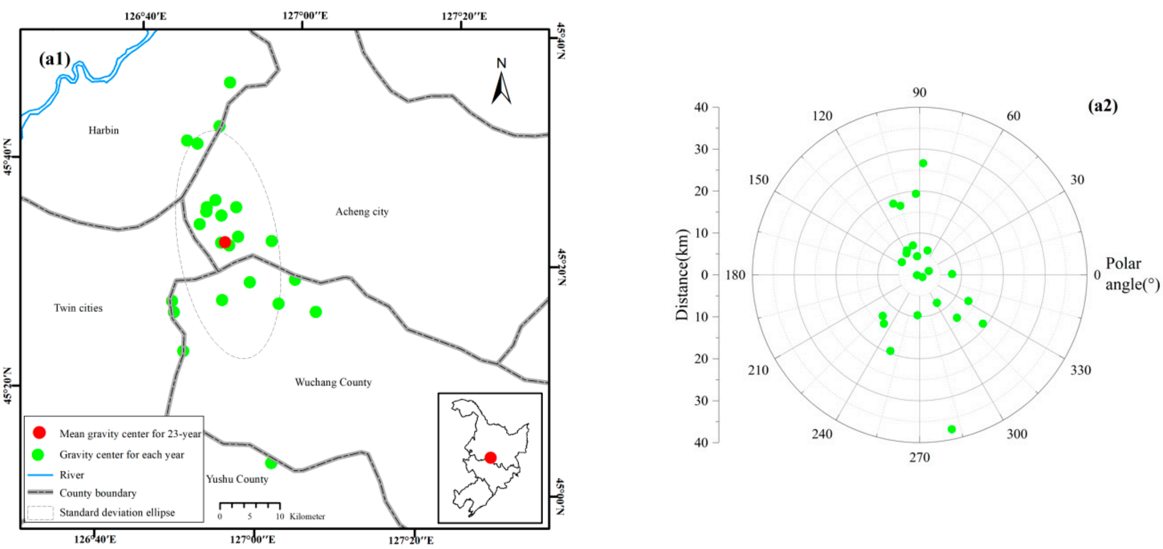
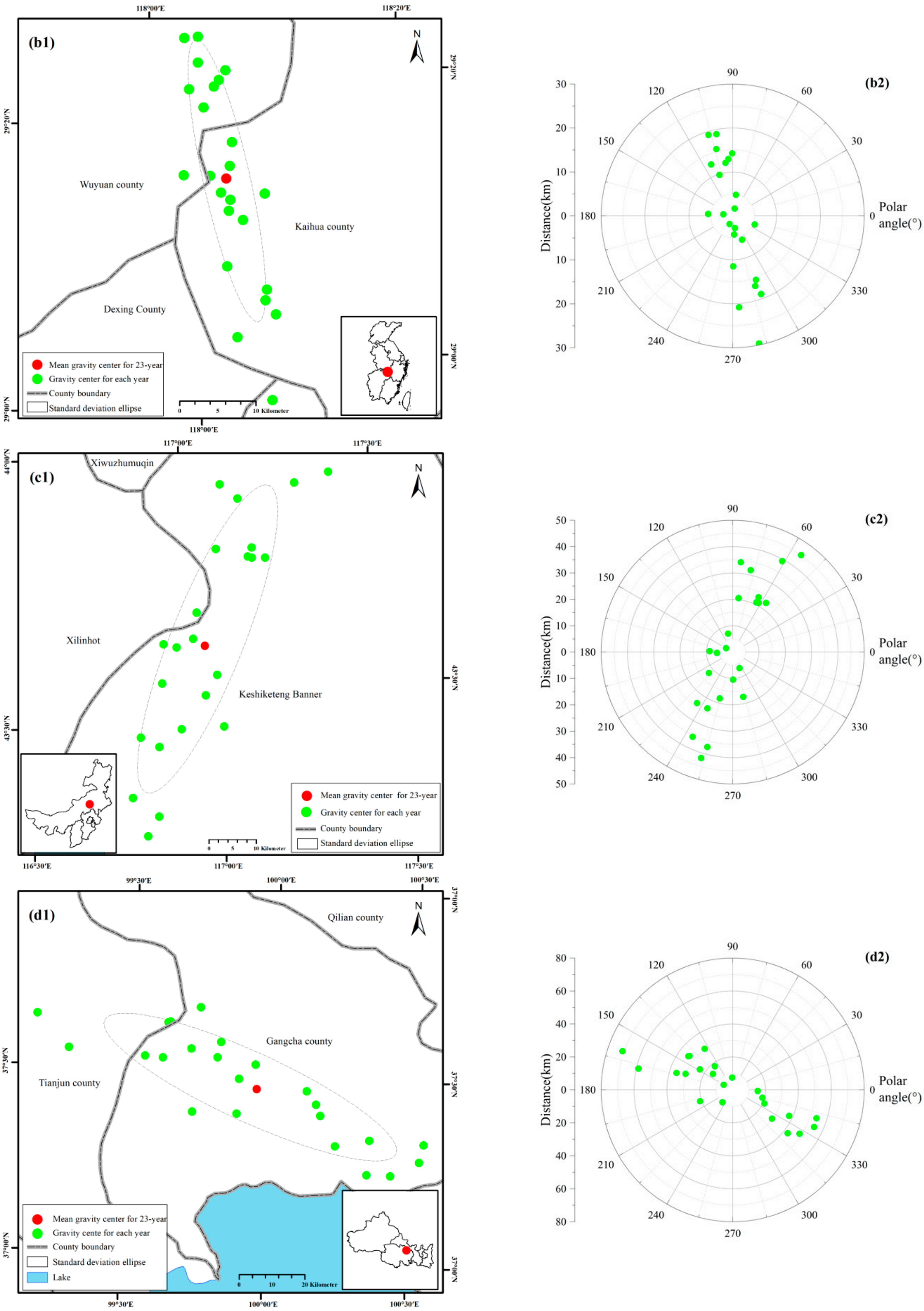


Figure 6. *Cont.*



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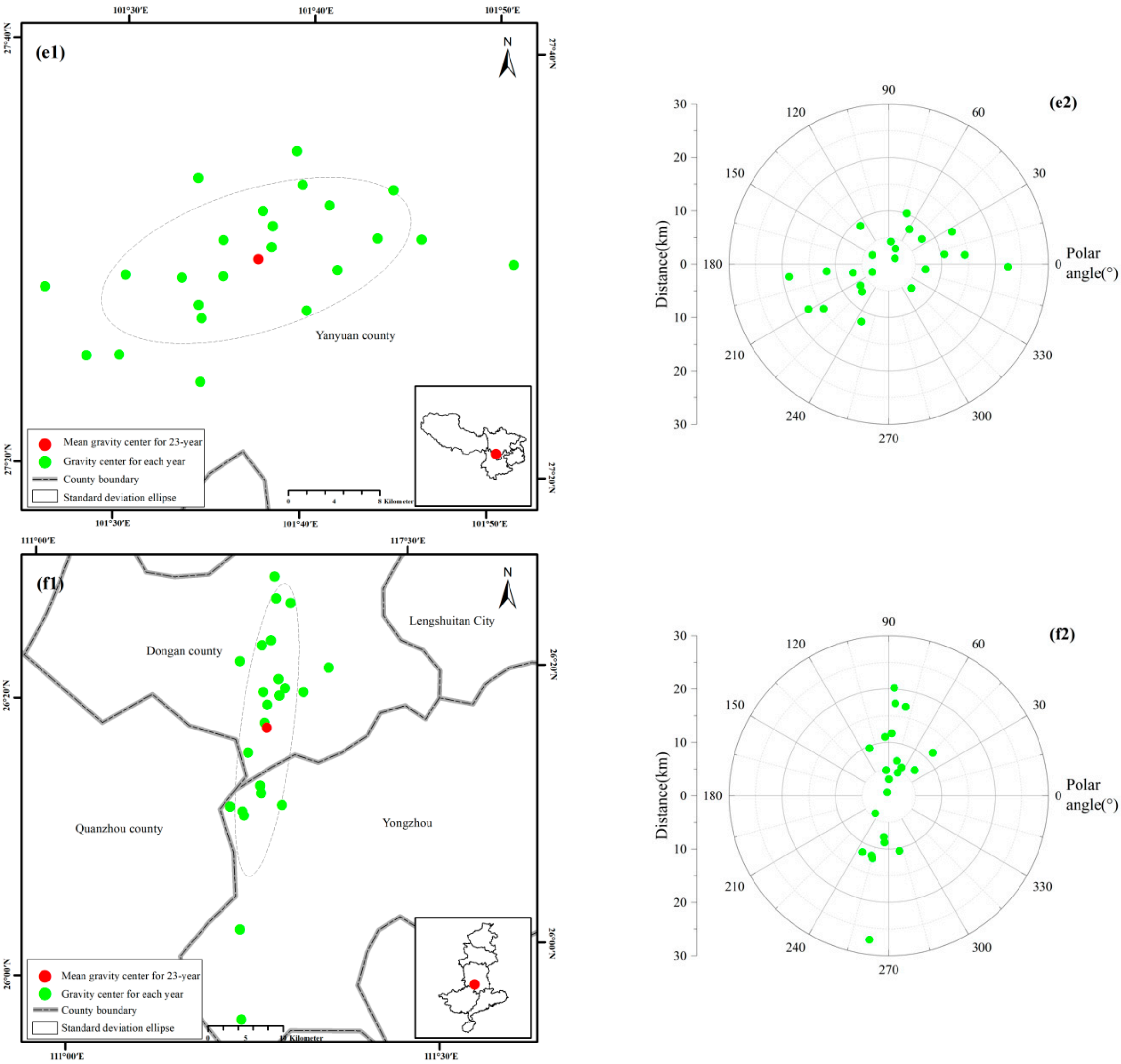


Figure 6. The vegetation NPP gravity centers in six regions of China. (**a1**) Northeast (space). (**a2**) Northeast (polar coordinates). (**b1**) East China (space). (**b2**) East China (polar coordinates). (**c1**) North China (space). (**c2**) North China (polar coordinates). (**d1**) Northwest China (space). (**d2**) Northwest China (polar coordinates). (**e1**) Southwest China (space). (**e2**) Southwest China (polar coordinates). (**f1**) Central South China (space). (**f2**) Central South China (polar coordinates).

Table 3. The standard deviation ellipse parameters of vegetation NPP in six sub-regions 2000 to 2022.

Standard Deviation Ellipse Parameters	Northeast China	East China	North China	Northwest China	Southwest China	Central South China
Rotating angle (°)	170.61	167.46	21.81	114.63	72.35	7.17
Standard deviation along x-axis (km)	8.317	3.068	7.702	48.940	14.128	3.532
Standard deviation along y-axis (km)	19.194	18.925	34.859	10.548	6.201	19.735
Ellipse area (km^2)	501.510	182.429	843.525	1621.792	275.257	219.001

The vegetation NPP gravity centers in Northeast China are mostly located in Acheng City and Heilongjiang Province (Figure 6(a1,a2)). The ellipse angle was 170.617°, and the gravity centers showed a northwest–southeast distribution pattern. The ellipse area was 501.510 km^2 (Table 3). Under the polar coordinates, the northern half of the gravity center (northwest and northeast quadrants) accounted for 56% of the total gravity centers, indicating that the vegetation NPP increments in the northern half were greater than that of the southern half. The western half of the gravity center (northwest and southwest quadrants) accounted for 56%, indicating that the vegetation NPP increments in the western half were greater than that of the eastern half.

The vegetation NPP gravity centers in East China are mostly distributed in Kaihua County, Quzhou City, and Zhejiang Province (Figure 6(b1,b2)). The standard deviation ellipse angle was 167.459°, which was significantly different from that of Northeast China (170.617°), showing a northwest–southeast distribution pattern. The standard deviation ellipse area of 182.429 km^2 was the smallest among the six distribution areas. The standard deviations were 3.068 km and 18.925 km along the x- and y-axes, respectively. In 2001, the gravity centers deviated the farthest (29.651 km) from the origin, distributed at the southern end, indicating that, in 2001, the vegetation NPP increments were more significant in the corresponding area.

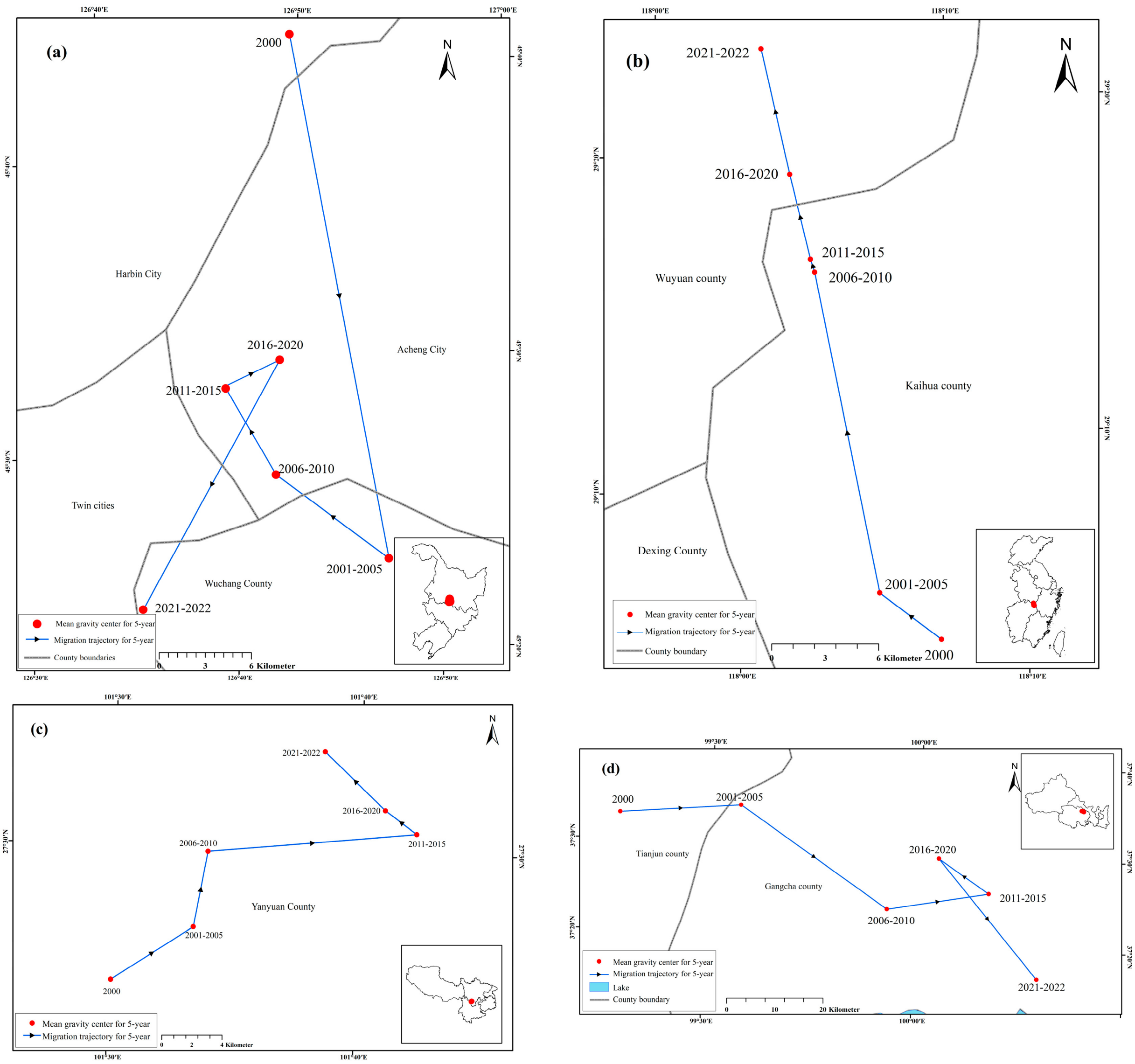
The vegetation NPP gravity centers in North China were concentrated in Keshiketeng Banner, Chifeng City, and Inner Mongolia (Figure 6(c1,c2)). The ellipse angle was small (21.81°), showing a northeast–southwest distribution pattern. The standard deviation ellipse area was large, indicating that the gravity center distribution in North China was more discrete. Approximately 56% of the gravity centers were distributed in the north.

The vegetation NPP gravity centers in Northwest China were mainly distributed in Gangcha County and Haibei Tibetan Autonomous Prefecture, with a standard deviation ellipse angle of 114.625°, showing a northwest–southeast distribution pattern (Figure 6(d1,d2)). The area of standard deviation ellipse was the largest, at 1621.429 km^2. The distribution was the most discrete. The gravity center was the farthest from the origin in 2001, with a distance of 70.931 km, indicating that, in 2001, the increase in vegetation NPP was more significant in the corresponding area. In the polar coordinate system, the distribution of the gravity centers in the north–south direction was relatively uniform. Most of the gravity centers were distributed in the northwest quadrant, indicating that the vegetation NPP increments in the northwest were greater than those in the southeast.

The vegetation NPP gravity centers in Southwest China were concentrated in Yanyuan County and Liangshan Yi Autonomous Prefecture, with a deflection angle of 72.350° (Figure 6(e1,e2)). The area of standard deviation ellipse was 275.257 km^2, and the dispersion degree was not large. According to the polar coordinate image, 2006 and 2015 had the farthest distances from the origin, at 18.857 km and 22.432 km, respectively, indicating that the vegetation NPP changed considerably in the corresponding area. Moreover, 2009 and 2012 had the smallest distances from the origin, at 3.412 km and 1.595 km, respectively, indicating that the vegetation NPP changed slightly in the corresponding area.

The vegetation NPP gravity centers in the central and southern regions were concentrated in Dong'an County and Yongzhou City, with a north–south spatial distribution (Figure 6(f1,f2)). The standard ellipse angle was 7.17°, and the standard ellipse area was small, indicating that its dispersion was small. The long axis of the standard deviation ellipse was 19.735 km in the north–south direction, and the short axis was 3.532 km in the east–west direction. The ratio was 5.59, indicating that the dispersion in the north–south direction was greater than that in the east–west direction. From the polar coordinates, it can be observed that the gravity centers in the northern quadrant had the largest proportion of 65%, indicating that the vegetation NPP increments in the northern half were higher than that in the southern quadrant. From the perspective of distance, in 2000 and 2001, it was far from the origin, and the distances were 27.237 km and 39.186 km, respectively, indicating that the vegetation NPP increased significantly in the corresponding areas in these two years. In 2006 and 2007, it was close to the origin, and the distances were 3.08 km and 0.69 km, respectively, indicating that the vegetation NPP did not fluctuate much.

Figure 7a shows that the vegetation NPP gravity centers in Northeast China showed a migration trend of southeast–northwest–northeast–southwest from 2000 to 2022. From 2001 to 2005, the gravity center shifted to the southeast compared with that of 2000, indicating that the vegetation NPP increments in the south were greater than those in the north. The vegetation NPP gravity center from 2006 to 2010 and 2011 to 2015 shifted to the northwest compared with that of 2001–2005, indicating that the increments of vegetation NPP in the northwest were greater than those in the southeast during the study periods. From 2016 to 2020, the gravity center shifted slightly to the northeast, indicating that the growth and increments of vegetation NPP in the northeast were greater than those in the southwest. From 2021 to 2022, the vegetation NPP gravity center shifted significantly to the southwest, indicating that the growth and increments of vegetation NPP in the southwest were greater than those in the northeast. On the whole, the vegetation NPP gravity center showed a trend of rotating from north to south to north and then moving south. However, the distance moving south was greater than that moving north, which indicates that the growth rate and increments in the south of Northeast China in the past 23 years were greater than those in the north.



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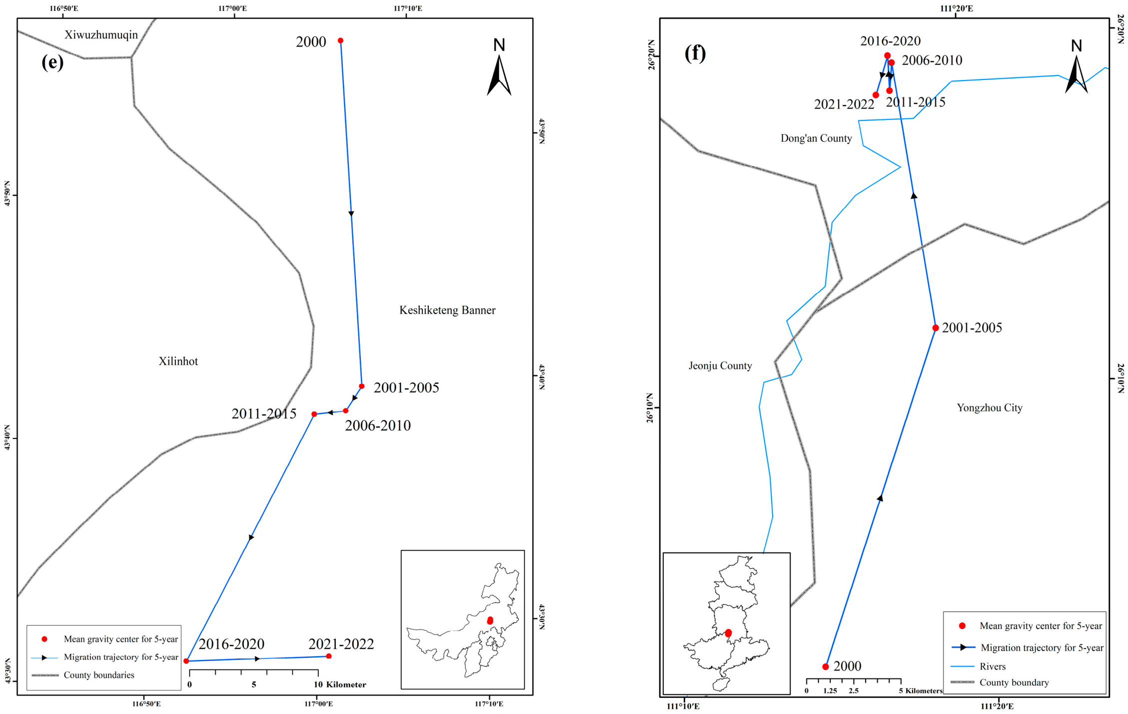


Figure 7. The migration trajectory of vegetation NPP center of gravity in six regions of China (5-year interval). (**a**) Northeast China. (**b**) East China. (**c**) Southwest China. (**d**) Northwest China. (**e**) North China. (**f**) Central South China.

Figure 7b shows that the gravity center migration trajectory of vegetation NPP in East China showed a trend of moving northwestward. During 2001–2005 and 2006–2010, the northwest migration distances were the largest, at 18.312 km, indicating that the growth rate and increments of vegetation NPP in the northwest direction were the largest during this period. During 2006–2010 and 2011–2015, the migration distances of the gravity center of vegetation NPP were the smallest, at 0.768 km, indicating that the growth rate and increments of vegetation NPP in the northwest direction were the smallest during this period.

Figure 7c shows that the vegetation NPP gravity centers in Southwest China moved northeastward in the first three periods and then moved northwestward in the last two periods. The five periods are 2000→2001–2005, 2001–2005→2006–2010, 2006–2010→2011–2015, 2011–2015, and 2016–2020→2021–2022. During 2006–2010 and 2011–2015, the migration distances were the largest, at 13.914 km, but the migration angle to the northeast was smaller, indicating that the growth rate and increments of vegetation NPP in the northeast direction were greater than those in the southwest direction during this period. During 2011–2015 and 2016–2020, the migration distances were the smallest, at 2.615 km. Overall, the gravity centers of vegetation NPP in Southwest China moved to the northeast, indicating that in the past 23 years, the increments of vegetation NPP in the northeast parts were greater than those in the southwest parts.

Figure 7d shows that the migration trajectory of the gravity centers in Northwest China was relatively complex. In 2001–2005, the vegetation NPP gravity center moved to the northeast. During 2001–2005 and 2006–2010, the gravity centers moved to the southeast, with the largest migration distance of 37.198 km, indicating that the vegetation NPP increments in the southeast parts were more significant. During 2011–2015 and 2016–2020, the gravity centers shifted to the northwest, and the migration distance was the shortest at 12.663 km, indicating that the increments and growth rate of vegetation NPP in the northwest parts were larger than those of other regions. Overall, the vegetation NPP gravity center moved to the southeast, indicating that the vegetation NPP increments and growth rate in the southeast parts were greater than those in the northwest parts.

Figure 7e shows that in 2001–2005, the gravity center of North China migrated to the southeast, with the largest migration distance of 26.884 km, indicating that the vegetation NPP increments in the southeast parts were higher than those in other parts. During 2001–2005 and 2006–2010, the gravity centers migrated to the southwest, with the smallest migration distance of 2.261 km, indicating that the vegetation NPP increments in the southwest parts during 2006–2010 were smaller than those in other years. Overall, the gravity center of vegetation NPP in North China showed a trend of moving southward.

Figure 7f showed that the change in vegetation NPP in the central and southern regions had a strong circuitry and complex change state. During 2000–2005, the gravity centers of vegetation NPP migrated to the northeast, with the largest migration distance of 18.837 km, and during 2001–2005 and 2006–2010, it moved to the northwest. During 2006–2010 and 2011–2015, 2011–2015 and 2016–2020, as well as 2016–2020 and 2021–2022, there was a trend of circuitous change. During 2006–2010 and 2011–2015, the gravity centers moved to the southwest, with the smallest migration distance of 1.488 km. During 2011–2015 and 2016–2020, the gravity center moved to the northwest. During 2016–2020 and 2021–2022, the gravity centers continued to move to the southwest. During the period from 2000 to 2022, the migration trajectory of the gravity center showed a trend of northeast–northwest–southwest–northwest–southwest. Overall, the vegetation NPP gravity center moved to the northeast.

3.4. Quantitative Discrimination of Climate–Human Effect on Vegetation NPP

The combined effects of climate-human interactions on vegetation NPP are examined through six scenarios. These six development scenarios were defined as areas with an increase in vegetation NPP via climatic change, human activities, and combined effects, as well as areas with a decrease in vegetation NPP via climatic change, human activities, and combined effects (Tables 3 and 4; Appendix A Figure A6).

Table 4. The area proportion of zones affected by climate–human interactions on vegetation NPP.

Relative Action Zone	Percentage (%) 2000–2010	Percentage (%) 2011–2022
NPP increased (climatic change)	23.87	36.03
NPP increased (human activities)	39.92	26.99
NPP increased (combined effects)	16.11	11.88
NPP decreased (climatic change)	12.89	9.09
NPP decreased (human activities)	5.00	14.29
NPP decreased (combined effects)	2.21	1.72

From 2000 to 2010, zones with human activities that promoted an increase in vegetation NPP had the largest proportion, comprising 39.92%, which was mainly distributed in Ningxia Hui Autonomous Region, Henan Province, and the junction of Heilongjiang Province and eastern Jilin Province. Zones with a reduction in vegetation NPP caused by combined effects had the smallest area, accounting for 2.21%, which was mainly distributed at the junction of Guangdong Province, Zhejiang Province, and Anhui Province. Overall, during 2000–2010, the proportion of areas with increased vegetation NPP was greater than that of areas with decreased vegetation NPP. From 2011 to 2022, zones with climate-change-promoted increases in vegetation NPP accounted for 36.03%, being mostly concentrated in Heilongjiang Province, Yunnan Province, Gansu Province, and southern Qinghai Province. Zones with a reduction in vegetation NPP caused by combined effects had the smallest area, accounting for 1.72%.

In contrast, among areas with an increase in vegetation NPP, zones with climate-change-promoted increases in vegetation NPP expanded significantly, while areas that underwent human-activity-promoted increases in vegetation NPP decreased significantly. These change areas were mainly distributed in Sichuan Province, Yunnan Province, Guizhou

Province, and Heilongjiang Province. For areas with a reduction in vegetation NPP, the proportion of zones with a reduction caused by human activities increased significantly.

We divided the climate-human contribution rate to the increase in vegetation NPP in the study area into five equal intervals: 0%–20%, 20%–40%, 40%–60%, 60%–80%, and 80%–100%. Firstly, 0%–20% indicates that the change in vegetation NPP (increase or decrease) was almost unaffected by human activities or climate change. Secondly, 20%–40% indicates that the change in vegetation NPP was slightly affected by human activities or climate change. Thirdly, 40%–60% indicates that the change in vegetation NPP was moderately affected by climate change or human activities. Fourthly, 60%–80% indicates that the change in vegetation NPP was strongly affected by climate change or human activities. Finally, 80%–100% indicates that the change in vegetation NPP was almost entirely affected by climate change or human activities (Appendix A Figure A7).

Figure 8 shows the region wherein climate change promoted an increase in vegetation NPP in 2000–2010, which was mainly distributed in North China (Figure 8a,b). In terms of climate change, the proportion of area with contribution rates greater than 80% was the largest, comprising 67.57%, which was mainly distributed in Heilongjiang Province, western Jilin Province, Shandong Province, Hebei Province, Anhui Province, eastern Qinghai Province, and northern Shanxi Province. Zones with a contribution rate between 20% and 40% had the smallest area, accounting for only 7.84%. Figure 8b and Appendix A Figure A7 showed that during 2000–2010, zones with an increase in vegetation NPP promoted by human activities were mainly distributed in southern China, and zones with contribution rates greater than 80% accounted for the highest proportion (77.29%), which were mainly in Guizhou Province, Sichuan Province, Henan Province, Yunnan Nasheng, Hubei Province, and eastern Inner Mongolia. Zones with contribution rates of 0%–20% and 60%–80% accounted for only 5.60%.

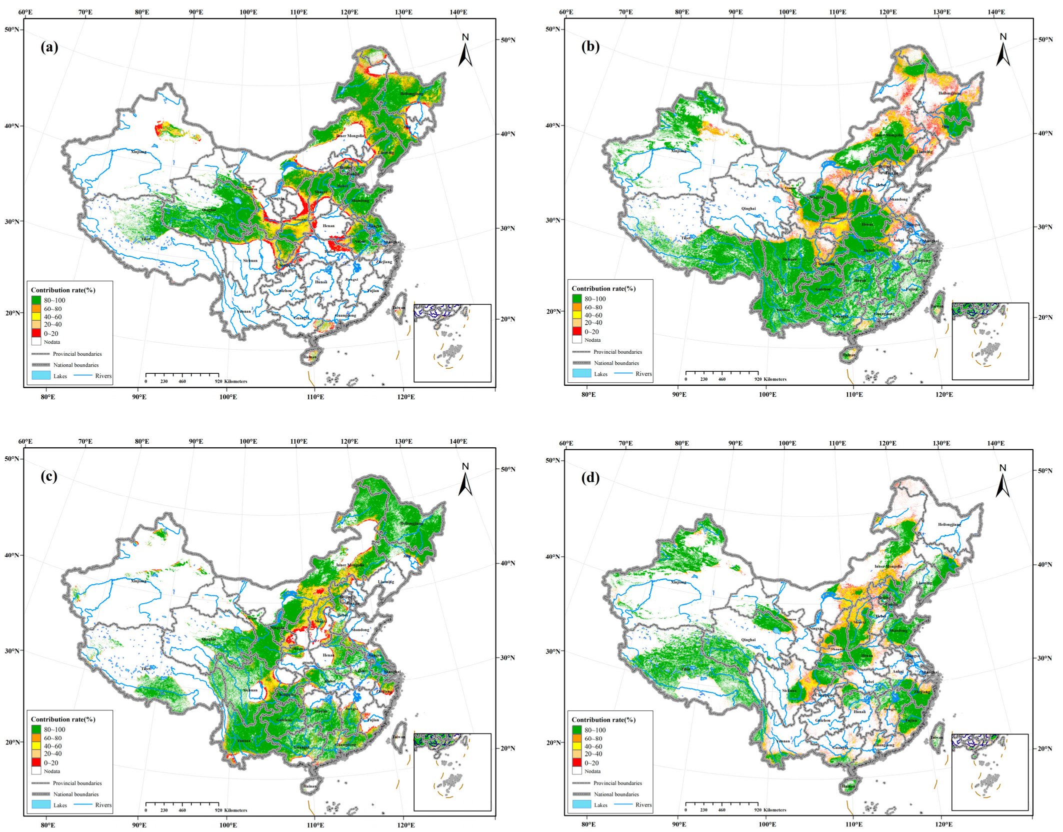


Figure 8. The spatial distribution of the contribution rate of climate–human interactions to the increase in vegetation NPP across different historical periods. (**a**) Climate change (2000–2010); (**b**) human activities (2000–2010); (**c**) climate change (2011–2022); (**d**) human activities (2011–2022).

From 2011 to 2022, climate change contributed 36.03% of the increase in vegetation NPP (Figure 8c,d). In terms of climate (Figure 8c), zones with contribution rates of 80–100% accounted for the largest proportion, comprising 79.78%, which were mainly distributed in Heilongjiang, Yunnan, Guangdong, Jiangsu, and Ningxia. Zones with contribution rates of 0%–20% had the smallest area proportion, comprising 4.22%. In terms of human activities (Figure 8d), zones with increases in vegetation NPP promoted by human activities were distributed in inland China, such as the patch areas formed by Shandong Province, Fujian Province, and Zhejiang Province; the Qinghai–Tibet Plateau; and the junction of Qinghai Province and Ningxia Hui Autonomous Region. From the perspective of contribution levels, zones with contribution rates of 80%–100% accounted for the largest proportion, at 74.65%, which were mainly located in each patch area, followed by zones with contribution rates of 40%–60%, accounting for 7.12%, which were mainly distributed at the junction of Shanxi Province and Inner Mongolia Autonomous Region.

Areas with a reduction in vegetation NPP caused by climate–human interaction are less extensive than areas with an increase in vegetation NPP, accounting for only 20.1% (Figure 9 and Appendix A Figure A8). In terms of climate change (Figure 9a), zones with contribution rates of 80%–100% had the largest area proportion, comprising 88.17%, which was mostly located in the southern part. The reduction in vegetation NPP caused by human activities was mostly located in the middle of the study area, such as the junction of Anhui Province and Zhejiang Province, southern Qinghai Province, and central and western Tibet (Figure 9b). Zones with contribution rates of 80%–100% accounted for the highest proportion, at 74.54%, which was mainly distributed in Guangdong and Guangxi. Zones with vegetation NPP decreases induced by climate change had larger areas than those caused by human activities. Our comprehensive analysis showed that the decrease in vegetation NPP during 2000–2010 was mainly related to climate change.

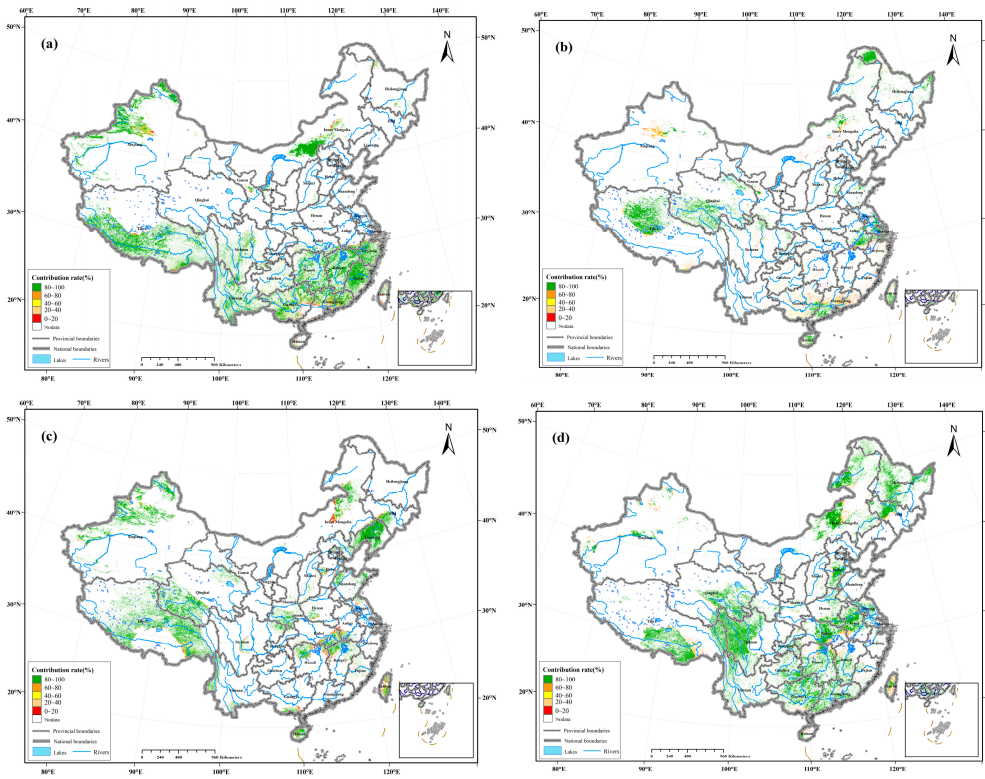


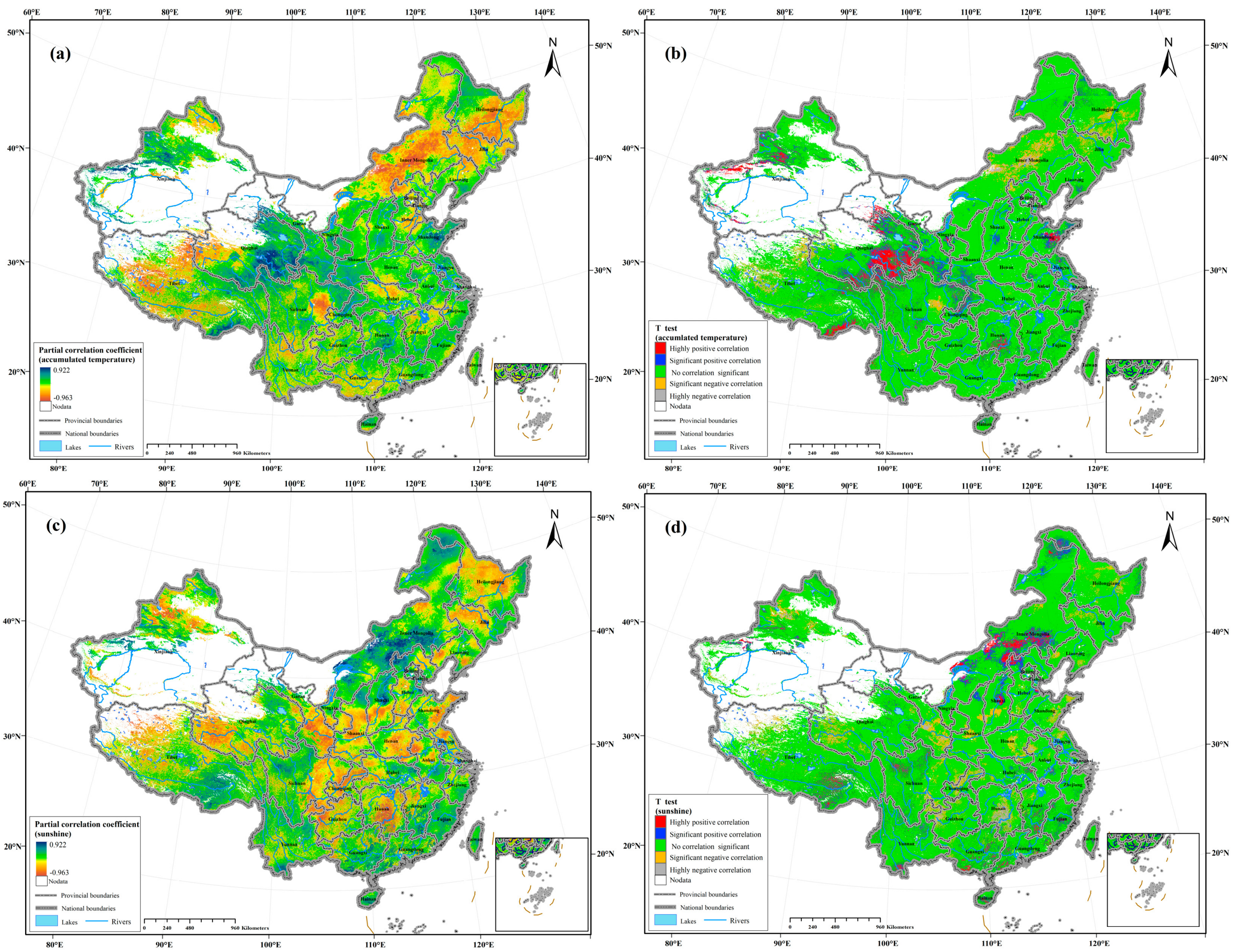
Figure 9. Spatial distribution of contribution rate of vegetation NPP decrease induced by climate–human interactions. (**a**) Climate change (2000–2010); (**b**) human activities (2000–2010); (**c**) climate change from (2011–2022); (**d**) human activities (2011–2022).

Areas with reduced vegetation NPP accounted for 25.1%, which was smaller than areas with increased vegetation NPP (Figure 9c,d). In terms of climate change (Figure 9c), zones with contribution rates of 80%–100% accounted for the largest proportion, at 86.81%, being mostly located in the southern part of the study area, such as the Tibet Autonomous Region, Jiangxi Province, and Hubei Province. Zones with contribution rates of 60%–80% were mostly located in the northern parts, accounting for only 2.80%. In terms of human activities (Figure 9d and Appendix A Figure A8), zones with contribution rates of 80%–100% accounted for the largest proportion, at 92.05%, which were mainly distributed across all provinces and cities. Zones with contribution rates of 0%–20% accounted for the smallest proportion, comprising only 1.78%.

3.5. Dominant Factors Influencing the Evolution of Vegetation NPP in Different Sub-Regions with Time Changes

3.5.1. Third-Order Partial Correlation Analysis

To further explore the correlations between vegetation NPP and climatic factors (accumulated temperature, sunshine, precipitation, and temperature) from 2000 to 2022, a third-order partial correlation coefficient was used to explore the relationships between vegetation NPP and climatic factors (Figure 10).



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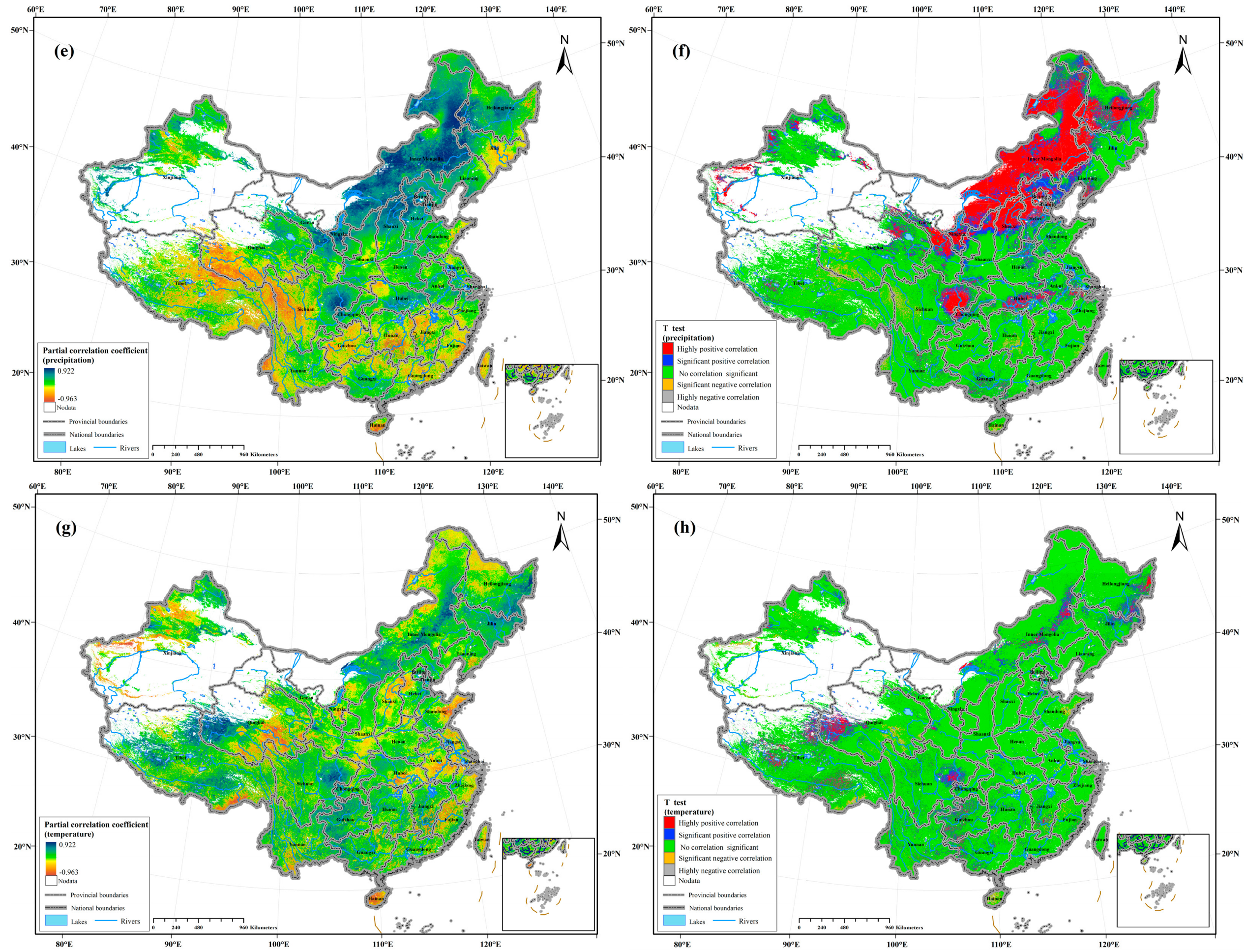


Figure 10. A partial correlation analysis distribution map and a significance test distribution map of vegetation NPP and climatic factors. (**a**) Vegetation NPP is partially correlated with accumulated temperature; (**b**) a significance test of vegetation NPP and accumulated temperature; (**c**) vegetation NPP is correlated with sunshine; (**d**) a significance test of vegetation NPP and sunshine; (**e**) vegetation NPP is partially correlated with precipitation; (**f**) a significance test of vegetation NPP and precipitation; (**g**) vegetation NPP is partially correlated with air temperature; (**h**) a significance test of vegetation NPP and temperature.

The third-order partial correlation coefficient between vegetation NPP and accumulated temperature ranged from −0.916 to 0.967. The positive correlation area accounts for 56.93%, which was mainly distributed south of the Yellow River and north of the Yangtze River, such as Henan Province, Shandong Province, and other regions (Figure 10a). Zones with negative correlation accounted for 43.06%, being mainly distributed in Jilin, Liaoning, and Tibet Autonomous Region. Figure 10c showed that the partial correlation coefficient between vegetation NPP and sunshine ranged from −0.953 to 0.940, of which the positive correlation area accounted for 47.76%, which was mostly concentrated in the northern part, such as Inner Mongolia, Loess Plateau, and northern Heilongjiang Province. Zones with negative correlation accounted for 52.24%, mainly concentrated in the southern part, such as Hunan Province and Guizhou Province. As shown in Figure 10e, the partial correlation coefficient between vegetation NPP and precipitation ranged from −0.954 to 0.974, of which the positive correlation area accounted for 71.67%, being mostly located in the northern parts, such as Inner Mongolia Autonomous Region, Heilongjiang Province, Shandong Province, and other regions. Zones with negative correlations accounted for 28.33%, which were mainly distributed in southern China, such as Fujian Province, Jiangxi Province, Hunan Province, and Guizhou Province. Figure 10g showed that the partial correlation coefficient between vegetation NPP and temperature was between −0.962 and 0.922, of which the positive correlation area accounted for 64.45%, being mainly distributed in the northern parts. Zones with negative correlations accounted for 35.55%, which were mainly distributed in southern China, such as Anhui, Zhejiang, Jiangsu, Fujian, and Hainan provinces.

Areas with extremely significant positive correlations between vegetation NPP and accumulated temperature accounted for 3.34%, and most of these areas were located in the Three-River Source Region. Areas with significant positive correlations accounted for 6.47%, most of which were located in the surrounding areas with significant positive correlations (Figure 10b). Zones with extremely significant negative correlations ($p < 0.01$, $R < 0$) accounted for only 1.15%, being mostly concentrated in the central and eastern parts of Inner Mongolia. Zones with significant negative correlations ($p < 0.05$, $R < 0$) accounted for 4.16%, which were mostly distributed in the Sichuan Basin, Qinghai–Tibet Plateau, and Songhua River–Nenjiang–Mudanjiang River Basin. According to Figure 10d, zones with extremely significant positive correlations in the partial correlation coefficient between vegetation NPP and sunshine accounted for 2.21%, which were mainly concentrated in Inner Mongolia. Zones with significant positive correlations accounted for 5.63%, and surrounding areas had extremely significant positive correlations. Zones with extremely significant negative correlation ($p < 0.01$, $R < 0$) had the smallest area proportion, at 1.97%, which were mainly distributed in internal areas with significant negative correlations. Zones with extremely significant positive correlation between vegetation NPP and precipitation partial correlation coefficient accounted for the largest proportion, comprising 16.94% in the significance level test (Figure 10f), being mainly distributed in North China, such as eastern Inner Mongolia, Loess Plateau, the Songhua River–Nenjiang River Basin, northern Hebei, and northwestern Shanxi. Zones with significant positive correlations accounted for 12.64%, mostly located in the surrounding areas with extremely significant positive correlations. Areas with significant negative correlations ($p < 0.05$, $R < 0$) accounted for 2.63%, which were scattered in southern China. Zones with extremely significant negative correlations ($p < 0.05$, $R < 0$) had the smallest area, accounting for only 0.96%. The zones with extremely significant positive correlations between vegetation NPP and temperature partial correlation coefficient accounted for 2.32% (Figure 10h), being widely distributed in northern Inner Mongolia, eastern Heilongjiang, Sichuan Basin, and the junction of Tibet Autonomous Region and Qinghai Province. Zones with significant positive correlations accounted for 7.74% and were distributed in the surrounding areas with extremely significant positive correlations. Zones with significant negative correlations ($p < 0.05$, $R < 0$) accounted for 2.04% and were scattered.

3.5.2. Dominant Factor Analysis

Single Factor

Factor detection can quantitatively determine the contribution rate of geographic factors on the spatial distribution difference of an index value. A factor detector of a geographic detector is used to analyze the q-value of each factor to obtain a single factor weight table.

As shown in Appendix A Figure A9a and Table 5, precipitation, soil type, and land use played a dominant role in vegetation NPP change in Northeast China in 2000, with q-values of 0.515, 0.461, and 0.443, respectively. The explanatory power of population density and GDP on vegetation NPP was smaller, with both less than 0.02. Appendix A Figure A9b and Table 5 show that, compared with 2000, the explanatory power changed to a certain extent. The dominant factors were land use, soil type, and altitude, with q-values of 0.456, 0.435, and 0.412, respectively. The influences of GDP and population density on vegetation NPP increased to a certain extent. However, the explanatory power of vegetation NPP was still small, with a q-value of no more than 0.1. Appendix A Figure A9c and Table 5 showed that land use, soil type, and slope were the dominant factors of vegetation NPP in Northeast China in 2022, with q-values of 0.440, 0.409, and 0.373, respectively. GDP and population density were the two factors with the smallest influence on vegetation NPP in Northeast China, with q-values of less than 0.3. It can be concluded that land use and soil type were the main factors affecting the changes in vegetation NPP in Northeast China.

Table 5. Q values for different regions in 2000, 2010, and 2020.

Region	Year	TEM	PRE	POP	GDP	ELE	GRA	LAND	SOIL
NEC	2000	0.181	0.515	0.007	0.018	0.439	0.346	0.443	0.461
	2010	0.102	0.205	0.011	0.071	0.412	0.384	0.456	0.435
	2020	0.097	0.281	0.02	0.029	0.332	0.373	0.44	0.409
NC	2000	0.485	0.584	0.005	0.004	0.160	0.237	0.580	0.714
	2010	0.43	0.705	0.005	0.011	0.19	0.249	0.649	0.736
	2020	0.344	0.673	0.004	0.015	0.175	0.265	0.621	0.732
EC	2000	0.441	0.372	0.094	0.053	0.341	0.303	0.347	0.39
	2010	0.393	0.256	0.08	0.164	0.307	0.276	0.349	0.347
	2020	0.356	0.237	0.056	0.058	0.298	0.273	0.326	0.323
NWC	2000	0.206	0.648	0.013	0.038	0.058	0.136	0.528	0.763
	2010	0.173	0.691	0.014	0.152	0.05	0.118	0.55	0.783
	2020	0.156	0.682	0.011	0.203	0.056	0.111	0.535	0.798
SWC	2000	0.719	0.776	0.137	0.011	0.713	0.03	0.454	0.753
	2010	0.729	0.706	0.003	0.099	0.736	0.029	0.486	0.773
	2020	0.766	0.744	0.002	0.078	0.77	0.023	0.508	0.801
CSC	2000	0.397	0.321	0.03	0.125	0.164	0.177	0.27	0.378
	2010	0.35	0.233	0.128	0.121	0.172	0.179	0.29	0.347
	2020	0.317	0.255	0.111	0.09	0.174	0.171	0.27	0.313

NEC—Northeast China; NC—North China; EC—East China; NWC—Northwest China; SWC—Southwest China; CSC—Central South China; TEM—temperature; PRE—precipitation; POP—population density; ELE—elevation; GRA—gradient; LAND—land utilization; SOIL—soil type.

Precipitation, land use, and soil type were the dominant factors affecting changes in vegetation NPP in North China in 2000, with q-values of 0.714, 0.584, and 0.580, respectively (Appendix A Figure A9a and Table 5). Slope and altitude exhibited little influence on changes in vegetation NPP, with q-values of 0.237 and 0.160, respectively. Similarly, population density and GDP showed little influence on vegetation NPP, with q-values less than 0.01. Appendix A Figure A9b and Table 5 showed that the dominant factors in 2010 were still soil type, precipitation, and land use, with q-values of 0.736, 0.705, and 0.649, respectively. Compared with 2000, the explanatory power of the dominant factors increased. The influence of altitude on vegetation NPP was insignificant, with a q-value of 0.190. The contribution rate of GDP and population density on vegetation NPP was still small, with q-values of 0.011 and 0.005, respectively. Appendix A Figure A9c and Table 5 showed that, compared with 2010, the dominant factors in 2022 did not change. The influence of altitude on vegetation NPP was still insignificant, with a q-value of 0.175. The influence of GDP and population density on vegetation NPP was still insignificant, with q-values of 0.015 and 0.004, respectively. We can conclude that soil type was the dominant factor affecting changes in vegetation NPP in North China.

The temperature in 2000, 2010, and 2022 was the main factor affecting changes in vegetation NPP, with q-values of 0.441, 0.393, and 0.356, respectively (Appendix A Figure A9). Compared with 2010, the explanatory power of precipitation decreased significantly, with a q-value reduction from 0.372 to 0.256. In 2020, the q-values of each factor decreased to varying degrees. The q-values of land use and soil types were roughly the same, with both around 0.32. GDP and population density had little impact on changes in vegetation NPP, with q-values less than 0.06. Temperature was the dominant factor influencing the variations in vegetation NPP in East China.

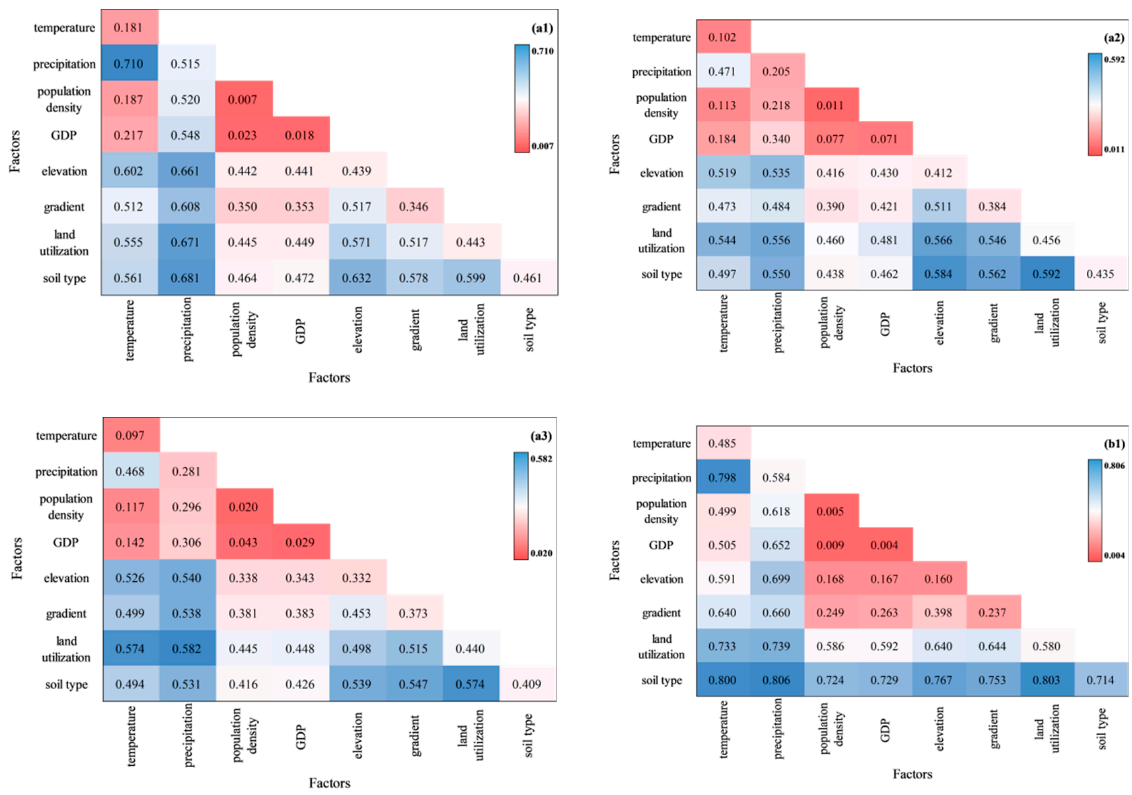
The dominant factor in 2000, 2010, and 2022 was soil type, with q-values of 0.763, 0.783, and 0.798, respectively (Appendix A Figure A9a and Table 5). The q-values of GDP increased significantly, indicating that human activities gradually became the dominant factors influencing vegetation NPP. Soil type, precipitation, and land use were the dominant factors influencing changes in vegetation NPP in Northwest China.

In 2000, the q-values of precipitation, soil type, temperature, and altitude affecting the changes in vegetation NPP were greater than 0.7 in Southwest China (Appendix A Figure A9a and Table 5). The q-values of slope and GDP were the smallest at 0.030 and 0.011, respectively, indicating an insignificant influence on vegetation NPP. Appendix A Figure A9b and Table 5 show that the dominant factors were soil type, altitude, temperature, and precipitation. Appendix A Figure A9c and Table 5 showed that the dominant factor did not change compared with 2010, and the q-values of the dominant factors increased to 0.801, 0.770, 0.766, and 0.744. The explanatory power of population density on the change in vegetation NPP was still the smallest, with a q-value of only 0.002. Soil type, altitude, temperature, and precipitation were the dominant factors influencing changes in vegetation NPP in Southwest China.

According to Appendix A Figure A9a and Table 5, temperature, soil type, and precipitation were the dominant factors in 2000 in central and southern regions, with q-values of 0.397, 0.378, and 0.321, respectively. Population density had the smallest explanatory power for vegetation NPP change, with a q-value of 0.03. Appendix A Figure A9b and Table 5 showed that, in 2010, the dominant factors were temperature and soil type, with q-values of 0.350 and 0.347, respectively. Appendix A Figure A9c and Table 5 showed that the dominant factors in 2022 were temperature and soil type, with q-values of 0.31, 0.317, and 0.313. Therefore, temperature and soil type were the dominant factors influencing changes in vegetation NPP in central and southern regions.

Interactive Factor

Interactive detection is a kind of geographical detector. The interaction between factors can be calculated using Formula (9). Interaction factor detection can be utilized to analyze the influence of interactions between different factors on changes in vegetation NPP (Figure 11). Using the origin to draw a color-scale diagram, the higher the value, the stronger the interaction between the representative factors, and vice versa.



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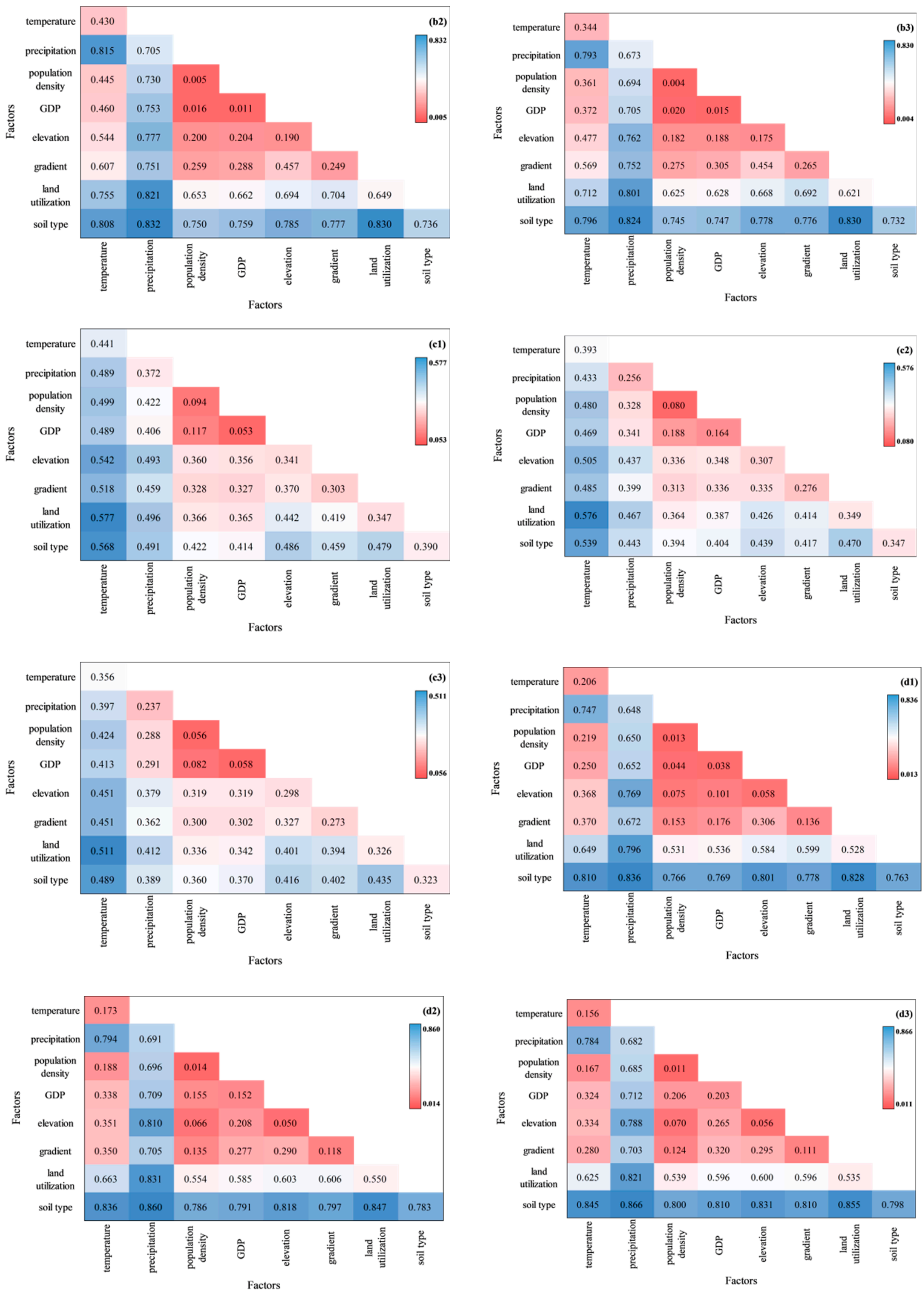

Figure 11. *Cont.*

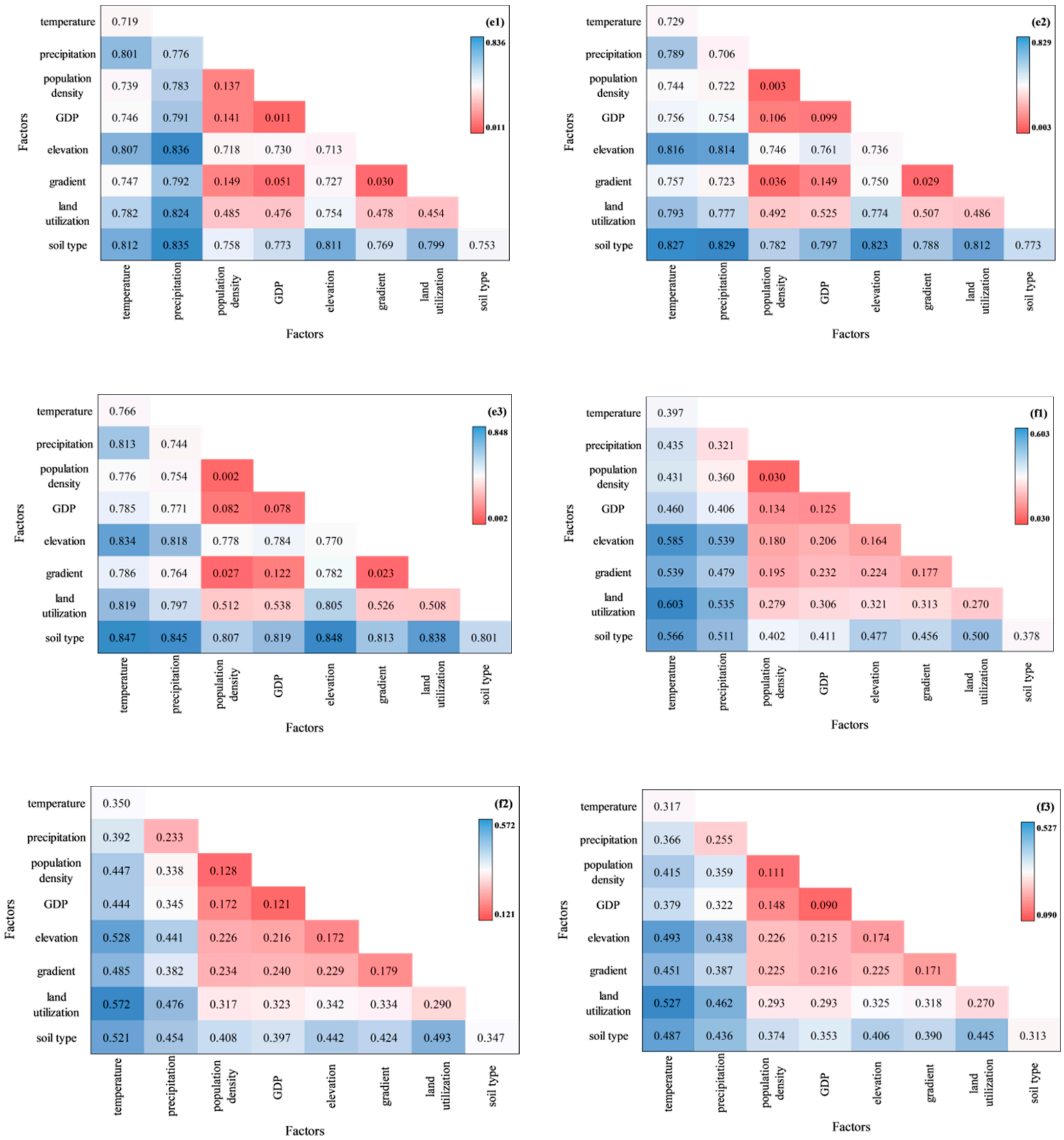

Figure 11. The interactive dominant factors affect vegetation NPP in different regions in different periods. (**a1**) Northeast China (2000). (**a2**) Northeast China (2010). (**a3**) Northeast China (2022). (**b1**) North China (2000). (**b2**) North China (2010). (**b3**) North China (2022). (**c1**) East China (2000). (**c2**) East China (2010). (**c3**) East China (2022). (**d1**) Northwest China (2000). (**d2**) Northwest China (2010). (**d3**) Northwest China (2022). (**e1**) Southwest China (2000). (**e2**) Southwest China (2010). (**e3**) Southwest China (2022). (**f1**) Central South China (2000). (**f2**) Central South China (2010). (**f3**) Central South China (2022).

Figure 11(a1–a3) shows that the interaction between the two factors in Northeast China is mostly mutually reinforcing. In 2000, the dominant interactive factor was temperature ∩ precipitation (0.710), while in 2010, land use ∩ soil type (0.592) became the dominant factor. In 2022, the dominant interactive factor was precipitation ∩ land use (0.582). As shown in Figure 11(b1–b3), in 2000 and 2010, the dominant interaction factor was precipitation ∩ soil type (0.806 and 0.832). In 2022, the dominant interactive factor was land use ∩ soil type (0.830). As shown in Figure 11(c1–c3), in 2000, 2010, and 2022, the dominant interactive factor was temperature ∩ land use (0.577, 0.576, and 0.511, respectively). As shown in Figure 11(d1–d3), in 2000, 2010, and 2022, the dominant interactive factor was precipitation ∩ soil type (0.836, 0.860, and 0.866, respectively). In general, the interaction between precipitation and soil type was the main factor affecting the change in vegetation

NPP in Northwest China. Figure 11(e1–e3) showed that in 2000, the dominant interactive factor was precipitation ∩ elevation (0.836). The dominant interactive factor in 2010 was precipitation ∩ soil (0.829), which changed significantly compared with that in 2000. The dominant interactive factor in 2022 was altitude ∩ soil type (0.848). Overall, the change in vegetation NPP in Southwest China was greatly affected by the interaction between altitude and precipitation, as well as other factors. As shown in Figure 9(f1–f3), in 2000, 2010, and 2022, the dominant interactive factor was temperature ∩ land use (0.603, 0.572, and 0.527, respectively). The interaction between GDP, population density, land use, and other factors showed a trend of strengthening first and then weakening. Overall, the interaction between temperature and other factors was the dominant factor affecting the change in vegetation NPP, and the influence of human activities on the change in vegetation NPP showed a trend of increasing first and then decreasing.

4. Discussion

4.1. The Reasons for the Spatio-Temporal Changes in Vegetation NPP

The spatial distribution of vegetation NPP during 2000–2022 was roughly the same as that in 2000–2010 and 2011–2022, showing a decreasing trend from south to north and from east to west, which is consistent with the research results of Shi et al. [39]. From the north to the south, the climate in southern China was hot and humid, and the precipitation was higher, which is conducive to vegetation growth. In the northern region, the climate type is mainly temperate continental. It was hot and rainy in summer and cold and dry in winter, and the vegetation growth environment was worse than that in the south, thus forming a spatial distribution pattern of high in the south and low in the north [18]. The western region of China was dominated by deserts and plateaus. The Taklimakan Desert and other regions had high temperatures all year round, scarce precipitation, and almost no vegetation coverage. Moreover, the Qinghai–Tibet plateau, with many glaciers and permafrost, had high altitude, low temperature, and scarce precipitation [16]. The vegetation type was dominated by alpine meadows, resulting in low levels of vegetation NPP. The eastern region was close to the Pacific and Indian Oceans. Due to the influence of ocean currents, the precipitation was richer than in the western region, and the vegetation types were more abundant. There were a small number of high-value areas in the northeast region and the southeast of the Qinghai–Tibet Plateau, which is consistent with the research results of Xue et al. [40]. Specifically, Northeast China had rich forest resources, high-quality black soil, and organic matter, which is conducive to the accumulation of vegetation NPP. At the same time, in 1998, China implemented the "Natural Forest Resource Protection Project", which further helped to improve vegetation NPP, resulting in a small number of high-value NPP areas in Northeast China. The southeast of the Qinghai–Tibet Plateau, with more precipitation than other parts, was affected by a Pacific monsoon, and its vegetation types were diverse.

In terms of time transfer from different grades, the transfer area from low to high accounts for a large proportion, and vegetation NPP showed an increasing trend, which is consistent with the research results obtained by Xu et al. [41] and Lou et al. [42]. This may be related to China's implementation of returning farmland to forest and grassland as part of its protection policy for ecological areas. NPP is a key factor in determining the ecological process of regulating carbon sources within ecosystems. It plays an important role in global change and carbon balance, providing insights for scientific decision-making in ecological management and climate change mitigation.

4.2. The Changes in Dominant Factors Influencing the Evolution of Vegetation NPP

Precipitation affects spatio-temporal changes of vegetation NPP in both dry and wet environments, temperature affects the rates of evaporation, and the synchronization of water and heat affects the growth state of the vegetation itself, thus affecting vegetation NPP. Compared with 2000–2010, human activities led to an obvious increase in areas with less vegetation NPP and a significant decrease in areas that promoted increases in vegetation NPP in 2011–2022 compared with 2000–2010. This might be due to the increase in human activities, including vegetation deforestation, corresponding with an improvement in living standards [39]. From the perspective of partial correlation, precipitation was mainly positively correlated in the north and negatively correlated in the south, which is related to the good hydrothermal conditions in the south and the cold and dry environment in the north. This is consistent with the research results of Guo et al. [26], which found a positive relationship between NPP and precipitation in Northeast China. In terms of temperature, zones with positive correlations were mainly located in the Qinghai–Tibet Plateau and Northeast China. Liu et al. [25] found that vegetation NPP of the Qinghai-Tibet Plateau was significantly positively affected by climate. Warm and humid climate change is an important driving force for the significant increase in vegetation NPP, which is consistent with the results of this study. Zones with negative correlations were mainly concentrated in the south, which is mainly related to the high latitude in Northeast China and the high altitude in the Qinghai–Tibet Plateau with low temperatures. An increase in temperature is conducive to plant photosynthesis and promotes the increase in vegetation NPP. In addition, precipitation and land use were the main factors affecting vegetation NPP in Northeast China, which is related to the high latitude and low precipitation in local areas. Due to the different research periods and driving factors, this is different from the research results obtained by Mao et al. [43]. In North China and Northwest China, precipitation and soil type were the main factors affecting vegetation NPP (the maximum q-values were 0.832 and 0.866, respectively). The main reason is that the soil type in North China is dominated by the river alluvial yellow dry farming type, which is consistent with the research results of Huang et al. [44]. The northwest region was mainly dominated by desertification, and precipitation was scarce, which was not suitable for vegetation growth. Precipitation became the dominant factor of changes in vegetation NPP in the northwest region. This is consistent with the research conclusion of Tong et al. [45]. The imbalance and uncertainty of the spatial and temporal distribution of water resources will lead to the contradiction between the ecological environment and economic development in the arid area of Northwest China.

The dominant factors in Southwest China were altitude and precipitation (the maximum q-value was 0.836). Xu et al. [30] found that precipitation had a strong enhancing effect on NPP in Southwest China, which is consistent with the results of this study. The local plateau area accounted for a large proportion, with high altitude, cold and dry climate, and mainly alpine meadow vegetation. The photosynthesis of vegetation was weak, which is not conducive to increases in NPP [46,47]. In Central South and East China, temperature and land use were dominant (the maximum q-values were 0.577 and 0.603, respectively). Although local precipitation and temperature levels were high, the temperature could not reach the dynamic balance of temperature and precipitation during vegetation photosynthesis, resulting in temperature being the dominant factor of vegetation NPP in Central South and East China.

From analyzing the impact of human activities, we determined that land use had more obvious impacts on changes in vegetation NPP in East China, Central and South China, and North China than other factors (the maximum q-values were 0.349, 0.290, and 0.649, respectively). In East China and Central South China, the rapid expansion of the population and urbanization had a great influence on the change in vegetation NPP. In North China, due to overgrazing, zones dominated by grassland were reduced, and desertification was aggravated, which is not conducive to an increase in vegetation NPP. Human activities had negative effects on vegetation NPP changes. Soil type had the greatest impact on the northwest region (the maximum q-value was 0.798). This region has the largest desert in China, which is not suitable for an increase in vegetation NPP [48–50]. The increase in human activities was conducive to the change in soil types and the increase in vegetation NPP. The influence of land use and population density on the change in vegetation NPP in Northeast China gradually increased. As the primary heavy industrial base in Northeast China, the region experienced rapid economic development, and human activities had negative effects on changes in vegetation NPP. Mao et al. [24] found that NPP changed greatly with the change in land use in Northeast China, which indicates that human activities have a significant influence on NPP. This is consistent with the results of this study. The influence of land use, GDP, and population density on changes in vegetation NPP in Southwest China was low (the maximum q-values were 0.508, 0.099, and 0.137, respectively), which was mainly due to the weak local economic foundations and the influence of human activities on vegetation NPP [51,52].

5. Conclusions

In this study, Geodetector, a gravity center model, and third-order partial correlation analysis methods were used to analyze the change patterns of vegetation NPP and its driving mechanisms in different sub-regions of China from a partition perspective.

(1) Vegetation NPP in China showed a decreasing trend from southeast to northwest. The gravity centers of Northeast, Northwest, and North China showed a trend of southward migration, indicating that the increments of vegetation NPP in the south of the corresponding region were greater than those in the north. The gravity centers of Southwest, Central South, and East China showed a trend of northward migration, indicating that the increments of vegetation NPP in the north of the corresponding region were greater than those in the south.

(2) During 2000–2010, human activities contributed greatly to the vegetation NPP increase and during 2011–2022, climate change was the dominant factor for the increase in vegetation NPP.

(3) Zones with significant positive correlations between vegetation NPP and accumulated temperature were mostly located in the southern part of Qinghai Province. Zones with significant positive correlations with precipitation were mostly concentrated in Inner Mongolia and other regions. Zones with significant positive correlations with temperature were widely distributed in the junction of Tibet and Qinghai Province and the northeast region. Zones with significant positive correlations with sunshine were mainly distributed in the central and eastern regions of Inner Mongolia.

(4) Precipitation and land use were the dominant factors influencing changes in vegetation NPP in Northeast China, while precipitation and soil types played an important role in the vegetation NPP changes in North China. Temperature was the dominant factor influencing the change in vegetation NPP in East China, while precipitation and soil types were the main factors affecting the vegetation NPP changes in Northwest China. The explanatory power of human activities on the change in vegetation NPP in Northwest China gradually increased. Altitude and precipitation contributed considerably to the change in vegetation NPP in Southwest China. Provided that urbanization is ensured, reducing land use can effectively promote an increase in local vegetation NPP.

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Data Availability Statement: Data are contained within the article.

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

Appendix A

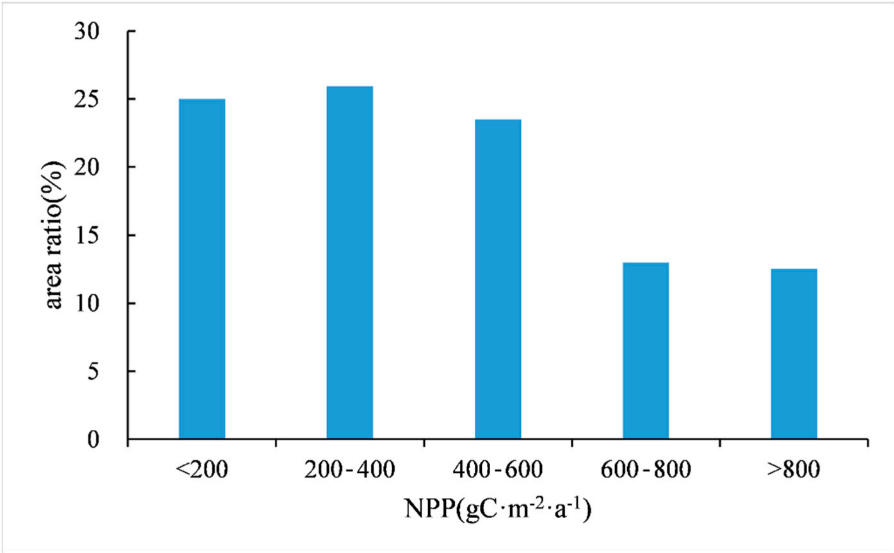

Figure A1. The proportion of different grades of vegetation NPP areas.

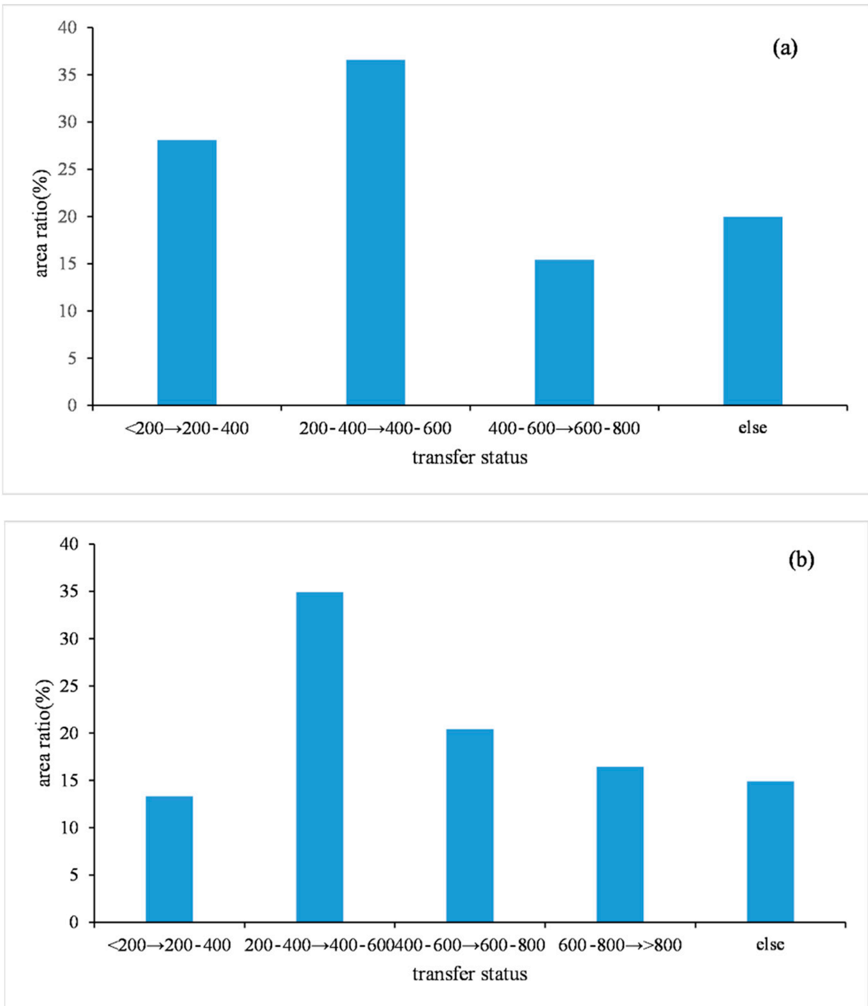

Figure A2. The proportion of different grades of vegetation NPP areas. (**a**) 2000–2010; (**b**) 2011–2022.

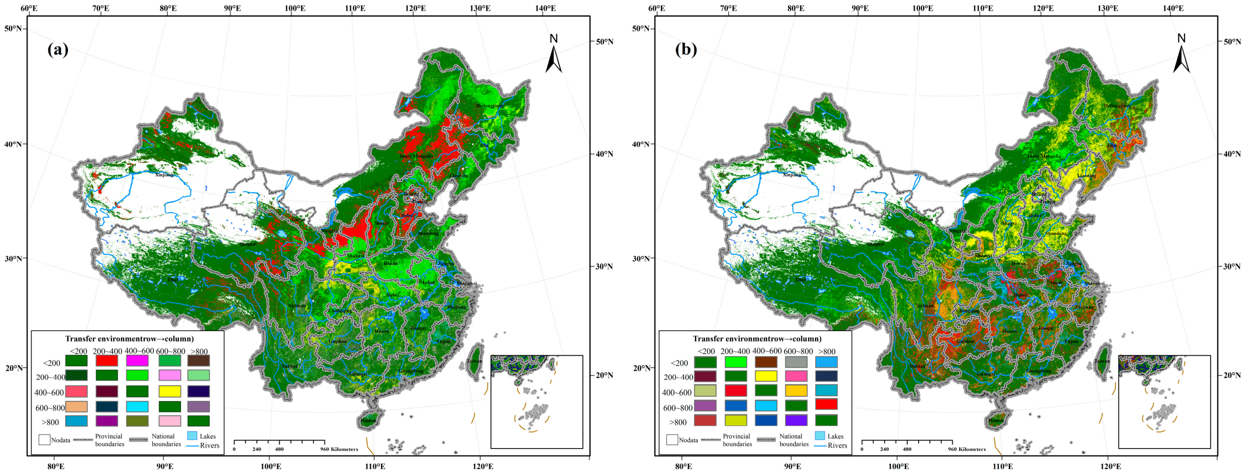

Figure A3. Conversion among different levels of vegetation NPP transfer at different levels. (**a**) 2000–2010; (**b**) 2011–2022.

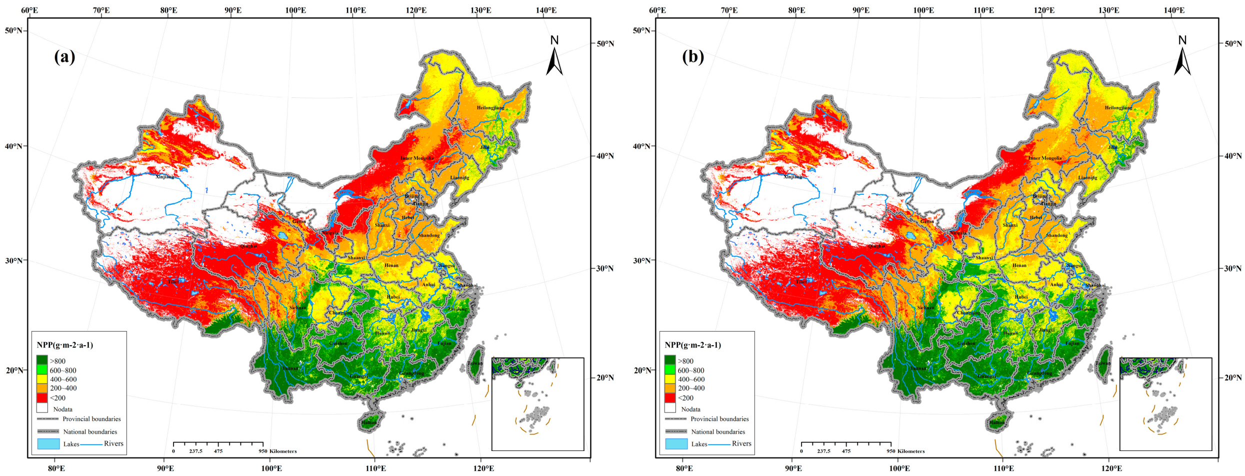

Figure A4. The mean distribution map of NPP at different levels during different historical periods. (**a**) 2000–2010; (**b**) 2011–2022.

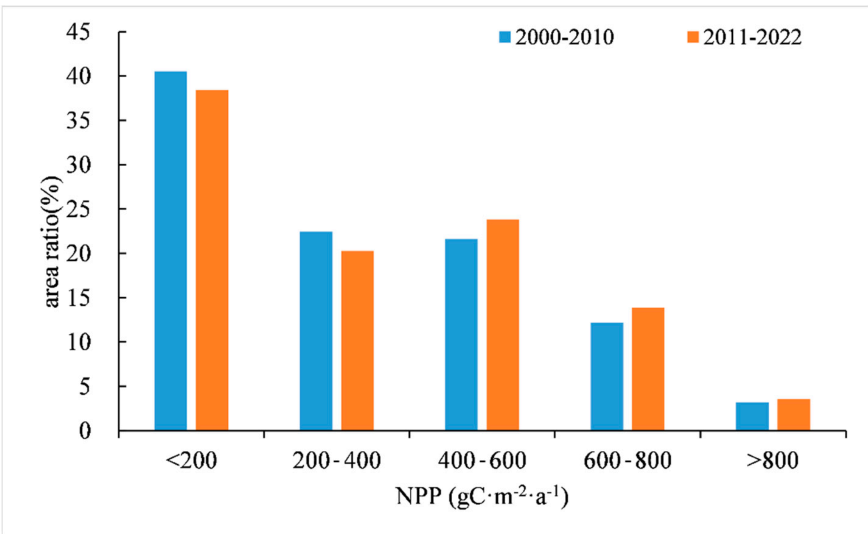

Figure A5. The area of different NPP levels during different historical periods.

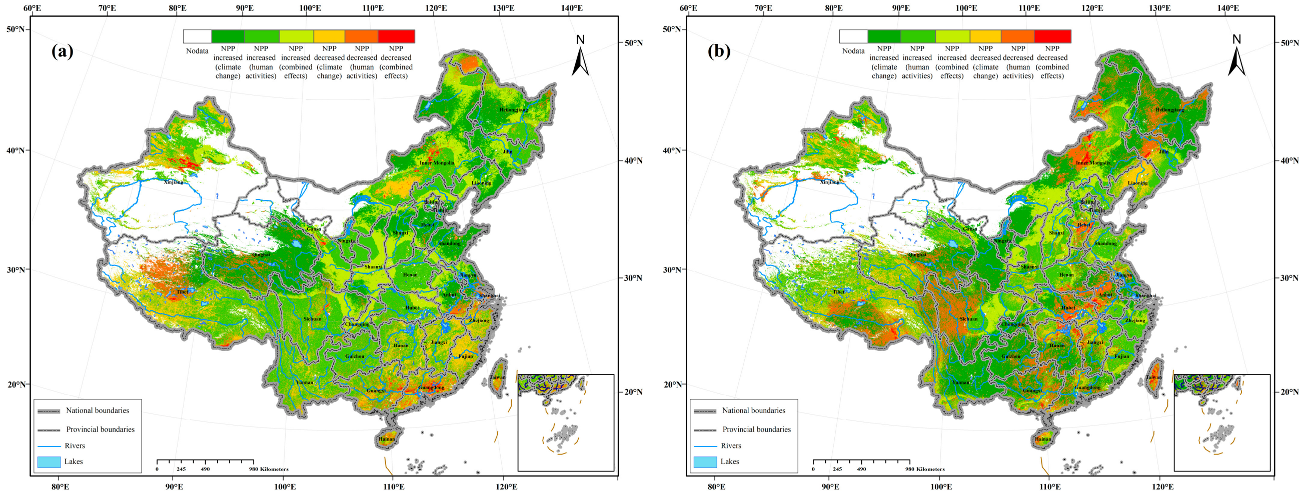

Figure A6. The spatial distributions of climate–human impacts on vegetation NPP. (**a**) 2000–2010; (**b**) 2011–2022.

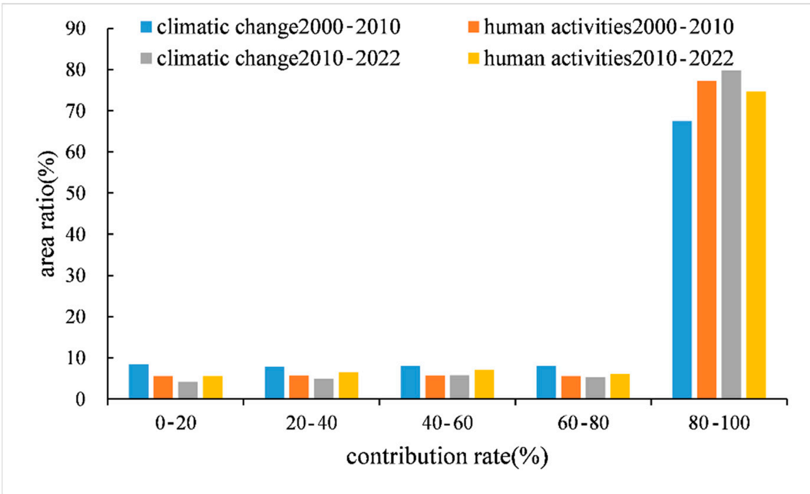

Figure A7. The area ratio of contribution rates for different grades during different historical periods (increase).

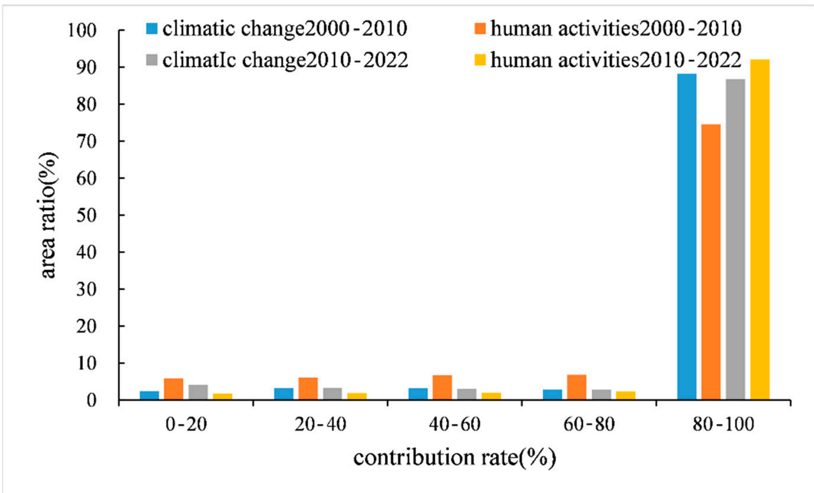

Figure A8. The area ratio of contribution rates for different grades during different historical periods (decrease).

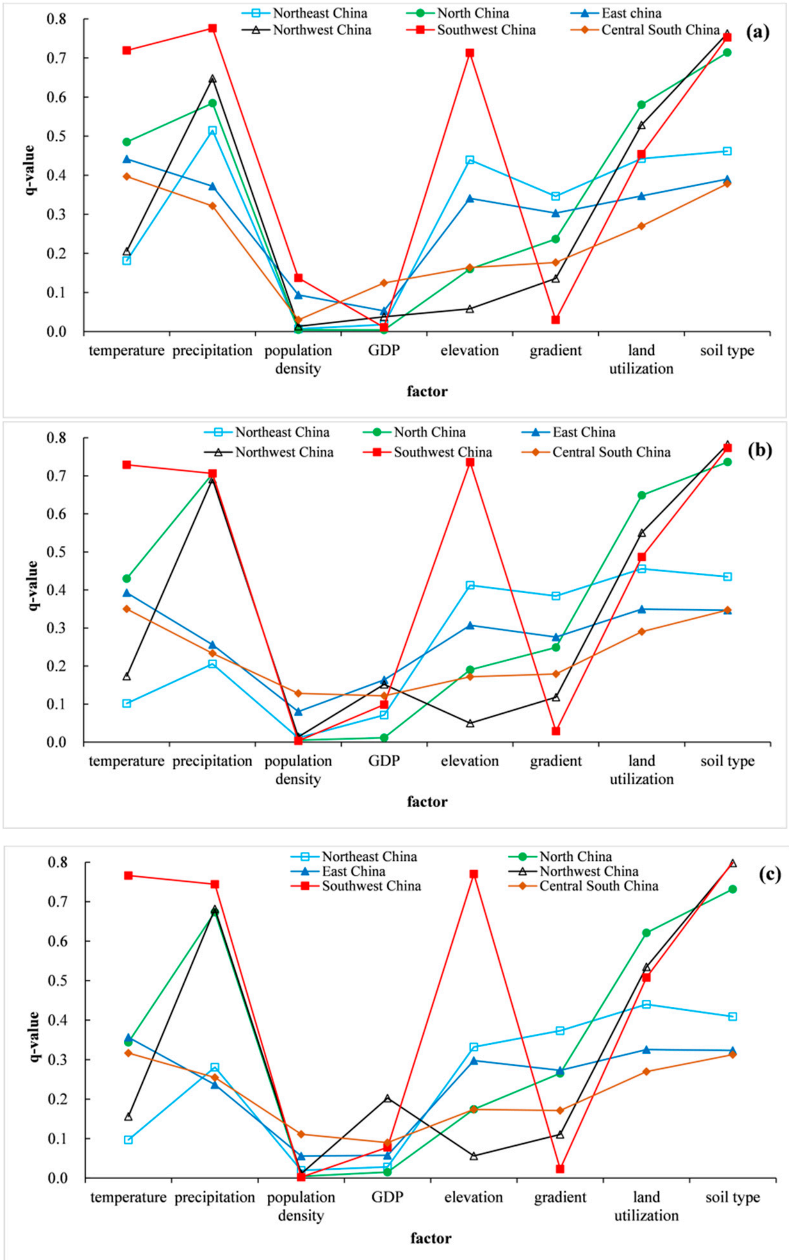

Figure A9. The explanatory power of each factor across different regions and years (q-value). (**a**) 2000; (**b**) 2010; (**c**) 2022.

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