forests

MDPI

Article

Analysis of Spatial-Temporal Changes and Driving Factors of Vegetation Coverage in Jiamusi City

Meibo Wang [1,2], Yingbin Wang [1], Zhijun Li [1,2,*] and Hengfei Zhang [1]

[1] School of Hydraulic and Electric Power, Heilongjiang University, Harbin 150080, China; 2211972@s.hlju.edu.cn (M.W.); 2222021@s.hlju.edu.cn (Y.W.); 2222023@s.hlju.edu.cn (H.Z.)
[2] Institute of Frigid Zone Groundwater, Heilongjiang University, Harbin 150080, China
* Correspondence: lizhijun78@163.com; Tel.: +86-13604513018

Abstract: This study of vegetation coverage in Jiamusi City provides theoretical support for local urban development, land use, and ecological environmental protection. Based on the land cover data and Landsat remote sensing image data from 2000 to 2020, the vegetation cover and land use data of Jiamusi City were extracted. The study includes the following aspects: (1) an analysis of the spatio-temporal changes in vegetation coverage; (2) analysis of the land use situation in Jiamusi City; and (3) investigation of the impact of natural and human factors on vegetation coverage in Jiamusi City using the Geodetector model. The results show that (1) over the past 20 years, the vegetation coverage of Jiamusi has shown a decreasing trend, declining from 25.22% in 2000 to 17.13% in 2020, representing a decrease of 32%. In terms of spatial distribution, the areas of Fuyuan City and Tongjiang City have experienced more significant decreases in vegetation coverage, decreasing by 73.6% and 54.0%, respectively. (2) The land use pattern of Jiamusi City has undergone significant changes during the study period; except for paddy fields (PF), unused land (UL), and construction land (CL), the areas of all the land categories have decreased. The ranking of the single land use dynamic degree in terms of magnitude is as follows: PF, UL, CL, dry farmland (DF), vegetation coverage land (VCL), and wetland (WET). (3) The changes in vegetation coverage were influenced by both natural and human activities and, according to the Geodetector results, the main influencing factors were CL and DF. The key findings of this study emphasize the need for comprehensive land use planning and ecological environmental protection that focus on sustainable development and conservation practices, and lay the groundwork for future ecosystem management and urban planning efforts in Jiamusi City.

Keywords: vegetation coverage; environmental change; human activities; Geodetector; land use

check for updates

Citation: Wang, M.; Wang, Y.; Li, Z.; Zhang, H. Analysis of Spatial-Temporal Changes and Driving Factors of Vegetation Coverage in Jiamusi City. *Forests* **2023**, *14*, 1902. https://doi.org/10.3390/f14091902

Academic Editor: José Aranha

Received: 22 August 2023
Revised: 10 September 2023
Accepted: 12 September 2023
Published: 18 September 2023

Copyright: © 2023 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (https://creativecommons.org/licenses/by/4.0/).

1. Introduction

Vegetation, an indispensable component of ecosystems, has a profound influence on human existence and development [1–3]. For example, it serves as an essential conduit for the absorption of atmospheric carbon dioxide through photosynthesis, thereby mitigating the greenhouse effect [4]. In addition, vegetation has a formidable capacity for soil and water conservation, reducing the damaging effects of rainfall erosion on land surfaces [5]. It also plays a crucial role in the diffusion of sound waves and the absorption of environmental noise, contributing to the reduction of noise pollution in our daily lives [6]. Finally, as an integral part of pollutant containment, vegetation adsorbs particulate matter and harmful substances in the atmosphere, thereby purifying the air [7–9]. However, with the acceleration of global economic and social development, coupled with urbanization, the vegetation area is gradually decreasing [10]. At the same time, global warming has intensified due to the significant increase in emissions of carbon dioxide and other greenhouse gases. If greenhouse gas emissions are not controlled, this could pose enormous risks to vegetation worldwide, especially in China [11]. Countries and organizations around the

world are gradually recognizing the dangers of decreasing vegetation coverage and are implementing a series of measures to protect vegetation. For example, in order to strengthen the conservation of forest resources and ensure the ecological safety of forests, China has continued to amend and improve the "Forest Law of the People's Republic of China" and Myanmar has launched initiatives such as the "Myanmar Reforestation and Rehabilitation Program" to protect and restore forest resources [2]. On 27 April 2017, the 71st United Nations General Assembly reviewed and approved the "United Nations Strategic Plan for Forests 2017–2030", the first-ever global forest development strategy under the auspices of the United Nations, underscoring the international community's high regard for forestry.

In recent years, China has faced serious soil degradation problems. In the northwestern region of China, extensive deforestation has led to severe soil erosion problems [12]. Due to prolonged excessive harvesting of forest resources, more than half of the world's original forests have degraded into secondary forests. This phenomenon is particularly severe in the northeastern region of China [13]. Jiamusi City is one of the last three remaining large black soil plains in the world, with pure water quality and excellent ecology. The arable land in Jiamusi City accounts for nearly one-third of the entire Sanjiang Plain, making it a renowned major producer of rice and soybeans, often referred to as the "Home of Chinese Soybeans" and the "Home of Northeast China Rice". However, due to the recent decline in vegetation coverage in Jiamusi City, there is a certain threat to the ecological environment. Deteriorating ecological conditions are unfavorable for crop growth. Therefore, studying the changes in vegetation coverage and its driving factors in Jiamusi City is of great importance to both the ecological environment and crop development.

Vegetation is highly sensitive to climate change and is also referred to as an "indicator" of global climate change [14,15]. Initially, the relationship between temperature and vegetation was a focus point of scholars' research. Sun et al. found that in the humid monsoon region of eastern China, air temperature is the main natural factor affecting vegetation changes [16]. Dong et al. found that temperature increases on the Qinghai–Tibet Plateau are unfavorable for vegetation growth [17]. In a study of the forest ecosystem in northeastern China, He et al. suggested that warmer temperatures could promote the growth of broadleaf species [18]. Li et al. studied tree species in the Changbai Mountain National Nature Reserve in China and found that the temperature increase had the same trend as the annual ring width of Korean pine [19]. As research continues, changes in vegetation coverage due to other climatic factors have also been brought to the attention of scientists around the world. Chen et al. found a positive correlation between precipitation and deciduous forests in humid or mountainous regions [20]. Sun et al. found that the frequency of precipitation, etc., may also have an effect on vegetation [21]. Wang et al. found that factors such as sunshine duration and precipitation have relatively small effects on vegetation degradation in their research in the lowland regions of southwest China [22]. By studying the radial growth of two dominant species on Changbai Mountain, Zhuang et al. found that increased precipitation can enhance the beneficial effects of temperature increase on Korean pine [23]. In addition, other studies have shown that human factors can have a significant impact on vegetation coverage. Hao et al. found that among the anthropogenic factors, population, and GDP had the greatest influence on the vegetation cover of coastal wetlands in China [24]. Yang et al. found that human activities were a key factor in the browning of vegetation through an analysis of the influencing factors on vegetation coverage in Ethiopia [25]. Based on previous studies and local conditions, this study first analyzed the vegetation coverage and land use changes in Jiamusi City. Then, it selected 11 influencing factors from natural and anthropogenic factors, where the natural factors include topography and climate, and the anthropogenic factors include population, economy, land use policy, and urbanization level. Jiamusi City is located in the cold zone of Northeast China, with significant fluctuations in precipitation and temperature. Therefore, this study selected average annual precipitation (AAP), annual average temperature (AAT), and elevation (ELE) as the three influencing factors from natural factors. In recent years, Jiamusi City has experienced continuous development of

modern agriculture, deepening industrialization, accelerated urbanization, and changes in land use. Based on these changes, this study selected PF, DF, WET, CL, GDP growth (GDP), average annual population fluctuation (AAPF), primary industry valued added (PIVA), and secondary industry fluctuation (SIF) as eight influencing factors from anthropogenic factors. The driving factors affecting the vegetation coverage in Jiamusi City were analyzed using Geodetector.

Geodetector, proposed by Wang Jinfeng et al., is a statistical method used to detect spatial variations and reveal the underlying driving forces [26,27]. Geodetector overcomes the limitations of traditional models based on linear assumptions and has found wide application in fields such as meteorology, land use, geology, and the environment. Using Geodetector for statistical analysis offers two main advantages: (1) it can capture both qualitative and numerical data and (2) it can explore the interactions between two factors and the dependent variable. Through this research, we can provide a theoretical basis for Jiamusi City's urban development and ecological environmental protection.

2. Materials and Methods

2.1. Study Area

Jiamusi is a prefecture-level city in Heilongjiang Province, located in the heartland of the Sanjiang Plain. It lies between 45°56′ N and 48°28′ N latitude and 129°29′ E and 135°5′ E longitude. Jiamusi City is divided into the Municipal District (Xiangyang District, Qianjin District, Dongfeng District, and Jiao District), Tongjiang City, Fujin City, Fuyuan City, Huanan County, Huachuan County, and Tangyuan County. The topography of Jiamusi gradually slopes from southwest to northeast, comprising the southern hilly region and the northern plain along the river. It belongs to the temperate continental monsoon climate zone, characterized by simultaneous rainy and hot seasons. The city's annual average temperature is about 3 °C, with long winters and short summers, and a frost-free period of about 146 days. The annual average precipitation is about 530 mm, and surface water resources are abundant. The location of Jiamusi City is shown in Figure 1.

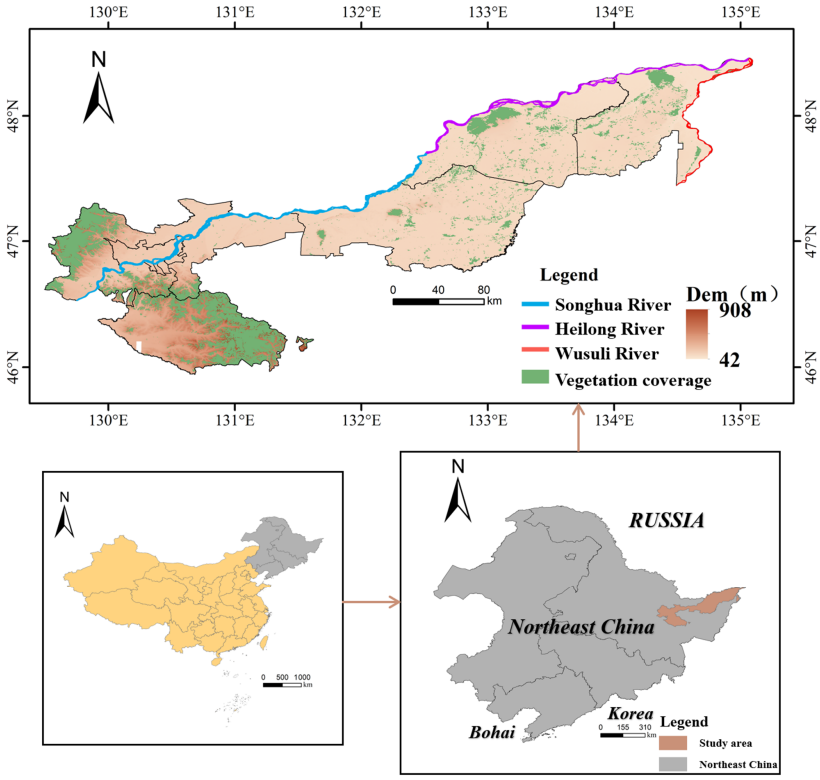


Figure 1. Location of the Jiamusi City.

2.2. Data Source

For this study, we downloaded land cover satellite images for the years 2000, 2005, 2010, 2015, and 2020 from the U.S. Geological Survey website (USGS, https://www.usgs.gov/, accessed on 1 May 2023). These images were obtained from Landsat 7 for the years 2000, 2005, and 2010, and Landsat 8 for the years 2015 and 2020. A spatial resolution of 30 m was achieved using Landsat 7's Enhanced Thematic Mapper Plus (ETM+) for earlier images, and Landsat 8's Operational Land Imager (OLI) for later ones. To process these images and perform land cover classification, we first performed preprocessing including radiometric calibration, atmospheric correction, and geographic correction. We then used a random forest classifier to classify these images. We identified six main land cover categories: PF, DF, VCL, WET, CL, and UL. Classification accuracy was evaluated by collecting ground truth data and creating a set of independent reference samples with high-resolution images. The overall classification accuracy was calculated using a confusion matrix and the Kappa coefficient, and an overall classification accuracy of 90.2% and a Kappa coefficient of 0.82 were obtained, indicating that the accuracy of our data is reliable. Data regarding temperature and precipitation for 2000–2020 were collected from the National Meteorological Information Center (http://data.cma.cn, accessed on 18 May 2023). The raster meteorological data were interpolated using ArcGIS 10.6 software, followed by the calculation of the AAT and AAP using the raster calculation tool in the software. A global digital ELE model (DEM) with a resolution of 30 m was downloaded from the Geospatial Data Cloud (http://www.gscloud.cn, accessed on 18 May 2023), and the DEM date was extracted using ArcGIS 10.6 software. Information on AAPF, GDP, PIVA, and SIF (2000–2020) was sourced from the China Statistical Yearbook of Resources and Environmental Sciences of the Chinese Academy of Sciences (http://stats.gov.cn, accessed on 23 May 2023) and the Jiamusi Statistical Yearbook; after spatial interpolation, the resolution was 1 km. Land use and land cover data (2000–2020) were obtained from the Resource and Environmental Science Data Center of the Chinese Academy of Sciences (http://www.resdc.cn, accessed on 18 May 2023). The spatial resolution is 30 m, and the land use types were divided into PF, DF, VCL, WET, CL, and UL. The Geographical data (research boundaries) were obtained from the National Geomatics Center of China (http://www.NGCC.cn, accessed on 18 May 2023).

2.3. Methodology

2.3.1. Land Use Analysis

By conducting the single land use dynamic degree analysis, it is possible to investigate the changes in land use types and examine the trends in vegetation land resources. The single land use dynamic degree refers to the rate of change of a specific land use type over a certain period, and can be calculated using the following formula [28]:

$$K = \frac{U_q - U_p}{U_p} \times \frac{1}{T} \times 100\% \quad (1)$$

In the formula, K (the single land use dynamic degree) is the rate of change of the land use type over the calculated time period, when the time period is 1 year, and K is the annual rate of change of the land use type. $K > 0$ indicates an increase in the land use type and $K < 0$ indicates a decrease in the land use type; U_p and U_q are the areas of certain land use type in the early and late period of the study, respectively and T is the study period length.

2.3.2. Geodetector

The core assumption of Geodetector is that if the dependent variable (Y) is greatly influenced by an independent variable (X), their spatial distributions should be similar [29,30]. This study primarily employed factor detection and interaction detection. The principles and calculation methods for both approaches are described below [31,32].

(1) Factor detection

Factor detection primarily involves exploring the magnitude of the driving force through a statistical measure, denoted as q. A larger value indicates a stronger explanatory power of X on Y, while a smaller value suggests a weaker relationship. When $q = 1$, it signifies that X completely controls Y, whereas $q = 0$ implies no association between X and Y. The q value ranges between 0 and 1, and its specific calculation method is provided as follows:

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

$$SSW = \sum_{h=1}^{L} N_h\sigma_h^2 \tag{3}$$

$$SST = N\sigma^2 \tag{4}$$

In the formula, h—stratification of Y or X, $h = 1, 2, 3, \ldots, L$; N—number of cells in the whole region; N_h—number of cells in stratum h; σ^2—variance of y-value in the whole region; σ_h^2—variance of h-values in stratification; SSW, SST—the sum of intra-stratification variance and the total variance in the whole region, respectively.

(2) Interaction detection

Interaction detection primarily aims to explore the magnitude of the impact of the combined effect of X_1 and X_2 on Y. The specific calculation process is as follows:

(1) Calculate the q values of X_1 and X_2 for Y, denoted as $q(X_1)$ and $q(X_2)$, respectively.
(2) Calculate the value of q during the interaction, denoted as $q(X_1 \cap X_2)$.
(3) Compare $q(X_1)$, $q(X_2)$ and $q(X_1 \cap X_2)$.

Based on the comparison results, several scenarios can be distinguished (Table 1).

Table 1. Categories of the interaction effect between X_1 and X_2 on Y.

Comparative Result	Interaction Type
$q(X_1 \cap X_2) < Min(q(X_1), q(X_2))$	Nonlinearity attenuation
$Min(q(X_1), q(X_2)) < q(X_1 \cap X_2) < Max(q(X_1), q(X_2))$	One-factor nonlinearity attenuation
$q(X_1 \cap X_2) > Max(q(X_1), q(X_2))$	Two-factor enhancement
$q(X_1 \cap X_2) = q(X_1) + q(X_2)$	Mutually independent
$q(X_1 \cap X_2) > q(X_1) + q(X_2)$	Nonlinear enhancement

In order to reveal the driving factors behind the changes in vegetation coverage in the Jiamusi region, 11 factors were selected for this study (AAP, AAT, PF, DF, WET, CL, GDP, AAPF, PIVA, SIF, and ELE) (Table 2). The change in vegetation coverage was used as the dependent variable, and the 11 driving factors were used as independent variables. Based on Create Fishnet in ArcGIS 10.6, 1 km × 1 km, 2 km × 2 km, 3 km × 3 km, 4 km × 4 km, and 5 km × 5 km grids were created. Subsequently, 10,450, 2750, 1215, 653, and 423 sample points were generated, and a 2 km × 2 km grid was determined as the optimal scale. Since the input variables to the Geodetector model can only be discrete, the selected factors were discretized and reclassified into six categories using the natural breakpoint method (Figure 2). Then, the data for all variables were extracted based on the location of the sampling points using the "Extract Values to Points" function in ArcGIS 10.6. The single-factor contribution of vegetation coverage sites was quantified, as well as the relationship between changes in vegetation coverage and the drivers.

Table 2. Factor of influence and its unit.

Factor of Influence	Unit
Average annual precipitation (AAP)	mm
Annual average temperature (AAT)	°C
Paddy fields (PF)	km^2
Dry farmland (DF)	km^2
Wetland (WET)	km^2
Construction land (CL)	km^2
GDP growth (GDP)	10^4 CNY/km^2
Average annual population fluctuation (AAPF)	Person/km^2
Primary industry valued added (PIVA)	10^4 CNY/km^2
Secondary industry fluctuation (SIF)	10^4 CNY/km^2
Elevation (ELE)	m

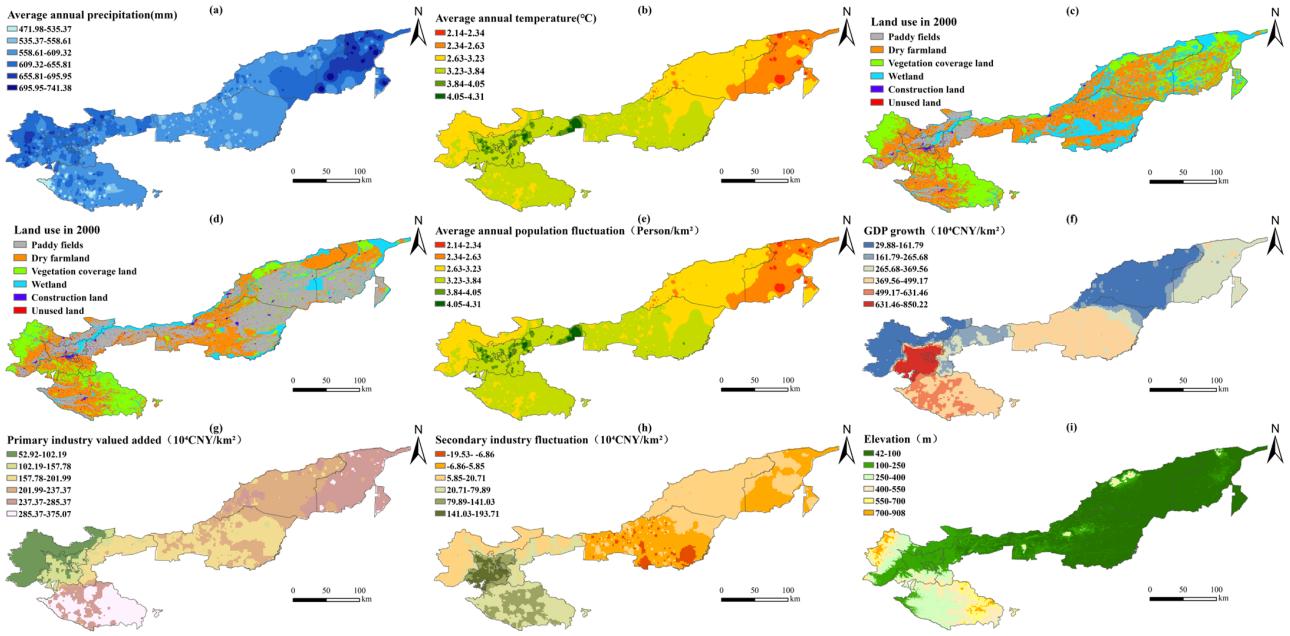


Figure 2. The spatial distributions of all factors in study area: (**a**) average annual precipitation (AAP); (**b**) average annual temperature (AAT); (**c**) land use in 2000; (**d**) land use in 2020; (**e**) average annual population fluctuation (AAPF); (**f**) GDP growth (GDP); (**g**) primary industry valued added (PIVA); (**h**) secondary industry fluctuation (SIF); (**i**) elevation (ELE).

3. Results

3.1. Analysis of Spatiotemporal Changes in Vegetation Coverage

The spatial and temporal changes in vegetation coverage in Jiamusi City are shown in Figures 3 and 4. In terms of temporal changes, the vegetation coverage in Jiamusi City showed a decreasing trend from 2000 to 2020. The decrease was relatively gradual from 2000 to 2005, while the most significant decrease occurred from 2005 to 2010. The rate of decline slowed down during the period from 2010 to 2020. This can be attributed to the implementation of the "Heilongjiang Forestland Protection and Utilization Plan (2010–2020)" in Jiamusi City. During this period, efforts were made to improve ecological management in ecologically fragile areas and actively restore forest vegetation. As a result, a significant decline in vegetation coverage was effectively prevented.

In terms of spatial distribution, the vegetation coverage in Jiamusi City is uneven. The highest vegetation coverage is observed in Huanan County and Tangyuan County in the northwest of Jiamusi City. On the other hand, the central region has the lowest vegetation coverage. The areas of Fuyuan City and Tongjiang City have experienced more significant decreases in vegetation coverage, decreasing by 73.6% and 54.0%, respectively.

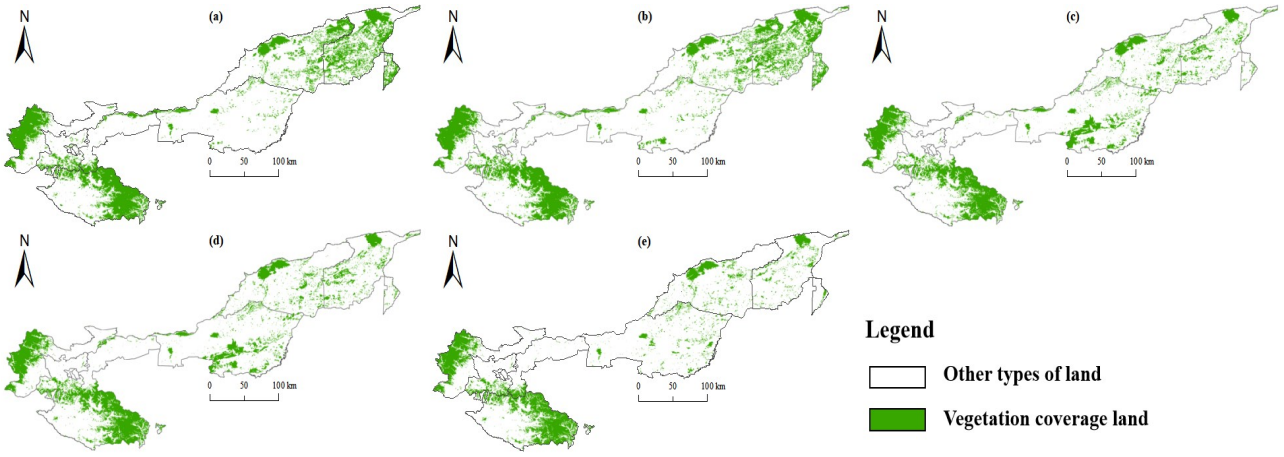


Figure 3. Spatial changes in vegetation coverage in Jiamusi City: (**a**) 2000; (**b**) 2005; (**c**) 2010; (**d**) 2015; (**e**) 2020.

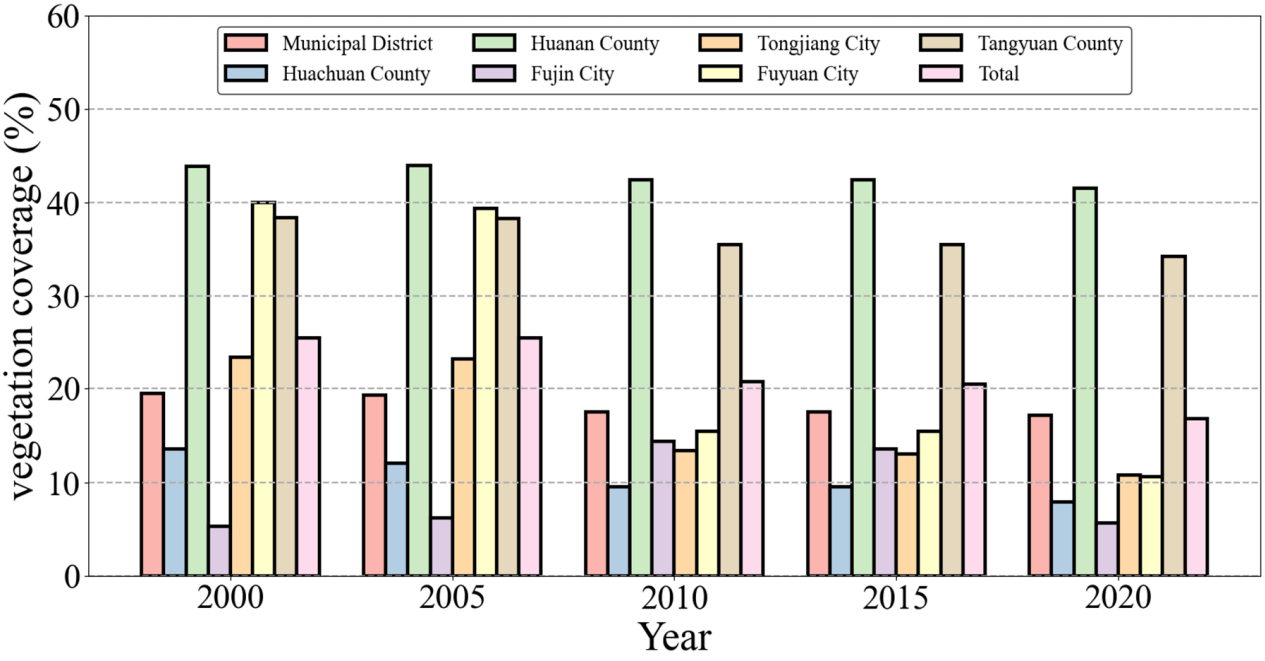


Figure 4. Characteristics of vegetation coverage changes over time in Jiamusi City: total (The area of vegetation in Jiamusi City/Area of Jiamusi City × 100%), Municipal District, Huanan Country, and Fuyuan City, etc. (the area of vegetation in Municipal District/area of Municipal District × 100%, the area of vegetation in Huanan Country/area of Huanan Country × 100%, the area of vegetation in Fuyuan City/area of Fuyuan City × 100%). Calculated as above for other areas.

3.2. Land Use Analysis

The land use changes in Jiamusi City is shown in Figure 5, the single land use dynamic degree is shown in Table 3. According to Figure 5, there have been significant changes in land use patterns in Jiamusi City from 2000 to 2020. Except for PF, UL, and CL, the areas of all the land types decreased. From 2000 to 2005, there was little change in the area of land use types, and the area of UL has not changed much. The area of PF increased slightly, while the areas of the other land types decreased slightly. From 2005 to 2010, the area of UL, PF, and CL increased, while the area of the other land types decreased. From 2010 to 2015, the area of UL has not changed much, while the area of PF and CL increased, and the area of the other land types decreased. From 2015 to 2020, except for the areas of PF and CL, the areas of all the land types decreased.

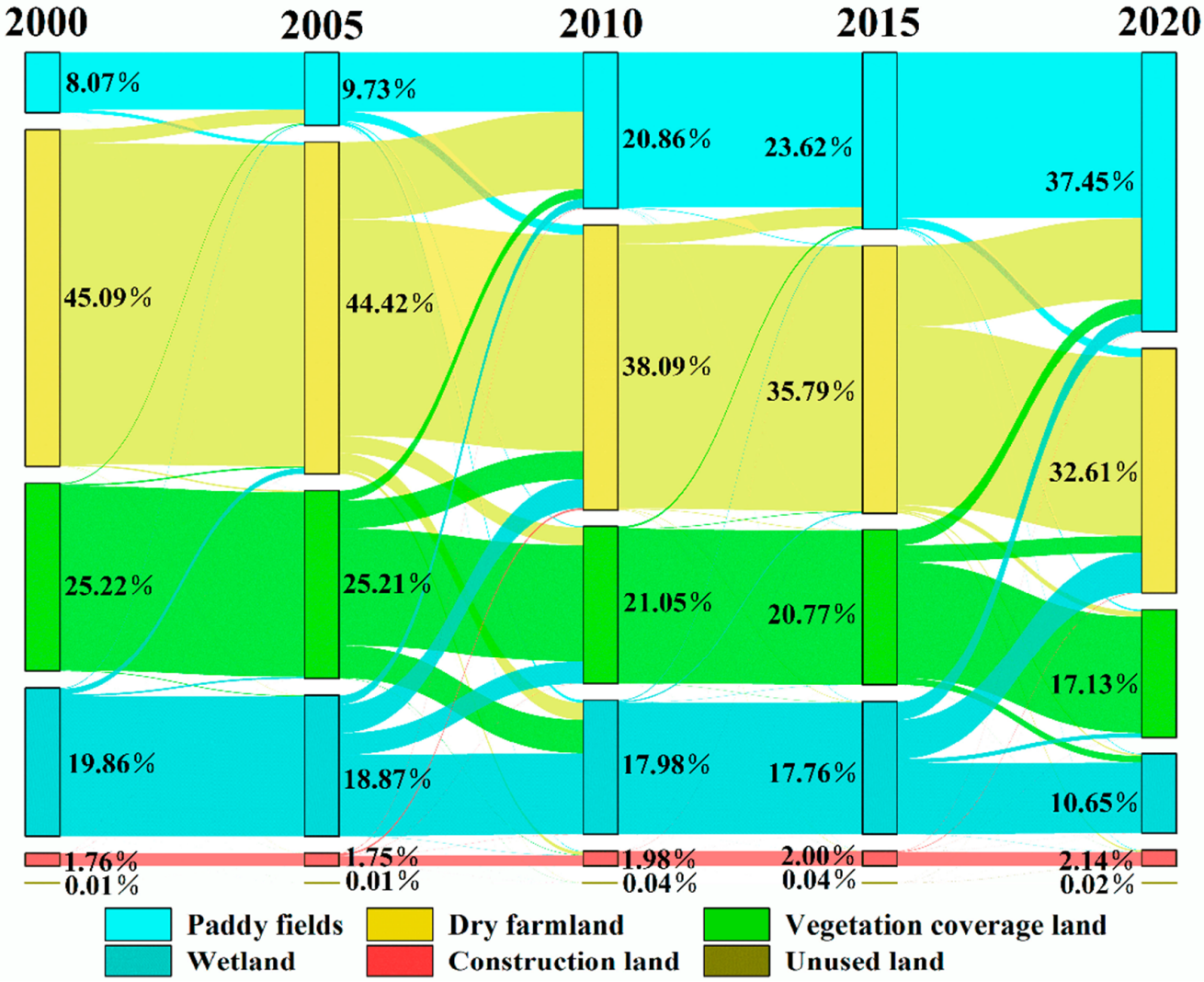


Figure 5. Land use changes in Jiamusi City from 2000 to 2020.

Table 3. The single land use dynamic degree (%).

Years	Paddy Fields (PF)	Dry Farmland (DF)	Vegetation Coverage Land (VCL)	Wetland (WET)	Construction Land (CL)	Unused Land (UL)
2000–2005	0.04115	−0.00298	−0.00004	−0.00992	−0.00008	0.01777
2005–2010	0.22875	−0.02848	−0.03302	−0.00941	0.02516	0.29607
2010–2015	0.02639	−0.01208	−0.00260	−0.00241	0.00288	0.04993
2015–2020	0.11714	−0.01780	−0.03507	−0.08013	0.01366	−0.10840
2000–2020	0.36399	−0.02768	−0.03206	−0.04638	0.02195	0.05456

According to Table 3, from 2000 to 2020, the ranking of Jiamusi City's single land use dynamic degree by size is as follows: PF, UL, CL, DF, VCL, and WET. Among them, PF, UL, and CL showed an increasing trend, with PF showing the most significant increase. DF, VCL, and WET showed a decreasing trend, with WET showing the most significant decrease. The single land use dynamic degree of VCL was −0.03206%, mainly due to the decrease in forest and grassland area over 2000–2020, resulting in a decrease in VCL. From 2000 to 2005, the single land use dynamic degrees of Jiamusi City had two positive and four negative values: PF and UL were positive, with an increase in area; DF, VCL, WET, and CL were negative with a decrease in area. From 2005 to 2010 and from 2010 to 2015, Jiamusi City's single land use dynamic degrees had three positive and three negative values: PF,

CL, and UL were positive with an increase in area; DF, VCL, and WET were negative with a decrease in area. From 2015 to 2020, the single land use dynamic degrees of Jiamusi City had two positive and four negative values: PF and CL were positive with an increase in area; DF, VCL, WET, and UL were negative with a decrease in area.

3.3. Driver Analysis

3.3.1. Analysis of Single Factor Detection Results

The results of the Geodetector calculations are shown in Table 4 and Figure 6. As illustrated in Table 4, the hierarchical order of explanatory power concerning the spatial variation of vegetation coverage within Jiamusi City from 2000 to 2020 is as follows: CL > DF > PF > AAT > ELE > PIVA > GDP > AAP > WET > SIF > AAPF. In the realm of human-induced factors, CL, DF, and PF exhibited coefficients of 0.42897, 0.38365, and 0.17565, respectively, thereby wielding an explanatory power surpassing 17%. These factors emerge as pivotal determinants profoundly shaping the vegetation coverage dynamics in Jiamusi City. This is because Jiamusi City is accelerating the construction of urban infrastructure, using roads to promote urban expansion, which will inevitably affect other land use types and have a significant impact on vegetation coverage. At the same time, Jiamusi City is also an important agricultural city, and the protection and expansion of agriculture will also affect the vegetation coverage. PIVA and GDP were 0.10512 and 0.10459, respectively, with an explanatory power of over 10%, indicating that they also had a significant impact on the vegetation coverage in Jiamusi City. However, the values of WET, SIF, and AAPF were 0.07565, 0.06889, and 0.03837, respectively, with explanatory powers below 10%, indicating a relatively small impact on vegetation coverage in Jiamusi City. Among these, AAPF manifests as the least influential contributor to vegetation coverage within Jiamusi City. This stems from the city's recent grappling with pronounced population diminishment and a concomitant decrease in population density. This trend gradually attenuates AAPF's sway over vegetation coverage. Among the natural factors, the values of AAT, ELE, and AAP were 0.13669, 0.12431, and 0.1021, respectively. Among the climatic factors affecting the vegetation coverage in Jiamusi City, AAT was the most important factor. This is because Jiamusi City is located in the cold zone of northeastern China with a long winter and cold climate, which significantly affects plant growth, making AAT the strongest explanatory factor for vegetation coverage among the climatic factors.

Table 4. The results of factor detection.

Factor of Influence	q Statistic
Average annual precipitation (AAP)	0.10210
Annual average temperature (AAT)	0.13669
Paddy fields (PF)	0.17565
Dry farmland (DF)	0.38365
Wetland (WET)	0.07565
Construction land (CL)	0.42897
GDP growth (GDP)	0.10459
Average annual population fluctuation (AAPF)	0.03837
Primary industry valued added (PIVA)	0.10512
Secondary industry fluctuation (SIF)	0.06889
Elevation (ELE)	0.12431

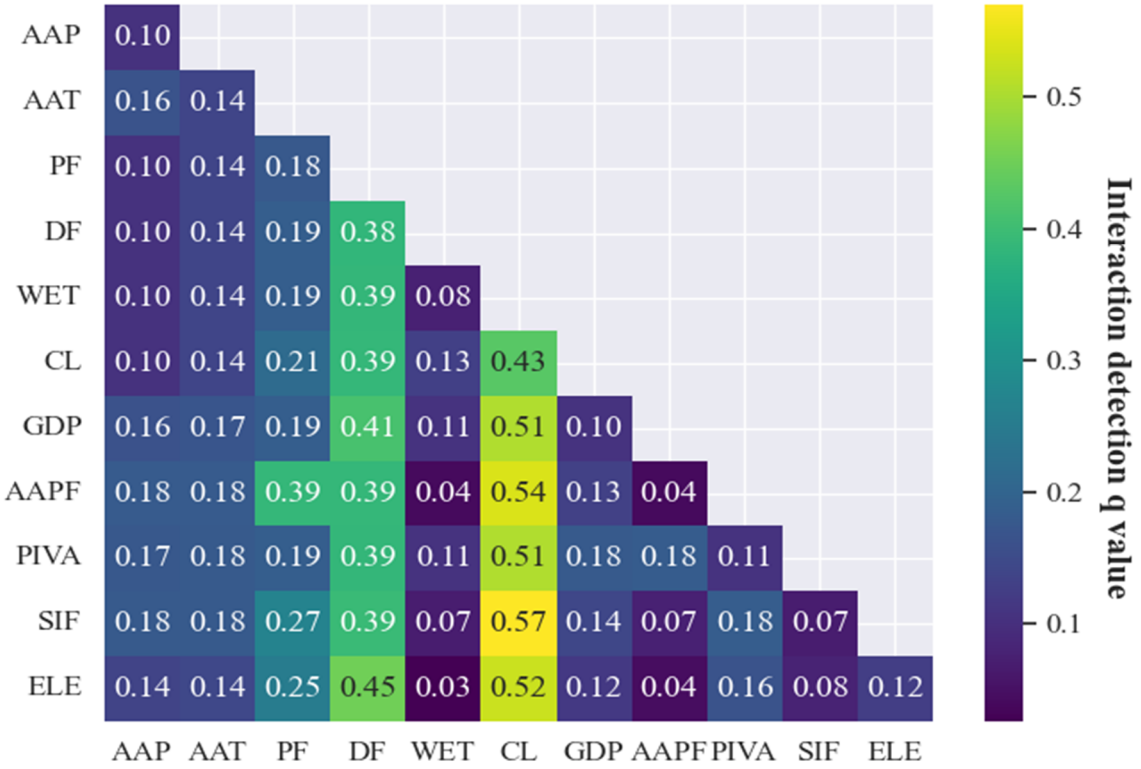


Figure 6. The results of factor interaction detection q value.

3.3.2. Detection of Factor Interactions

Based on the Geodetector calculations, it can be observed that in the interaction of two factors affecting vegetation coverage in Jiamusi City from 2000 to 2020, nonlinear enhancement relationships account for 21.8%, while two-factor enhancement relationships account for 78.2%. This indicates that the vegetation coverage in Jiamusi City is the result of the combined effect of multiple factors, and the interaction of any two influencing factors has a greater effect on the spatial distribution of vegetation coverage than a single factor. From Figure 6, the five pairs of factors that have the highest explanatory power for the vegetation coverage in Jiamusi City as a two-factor interaction, in descending order, are the interaction between CL and GDP, which reached a value of 0.51; the interaction between CL and AAPF, which reached a value of 0. 54; the interaction between PIVA and CL, which reached a value of 0.51; the interaction between CL and SIF, which reached a value of 0.57; and the interaction between CL and ELE, which reached a value of 0.52. Among them, the interaction between CL and SIF had the highest value. On the other hand, the interaction between WET and ELE had the lowest value, which was 0.03. Although the explanatory power of AAPF as a single factor is low, its explanatory power improves when it is interacts with other factors.

4. Discussion

Accurate and continuous monitoring of changes in vegetation cover and its spatial distribution is of great importance for global ecosystem and climate change research [33]. In this context, remote sensing technology, especially Landsat high-resolution imagery, has gradually become an essential tool due to its ability to provide detailed observations over time and space [34,35]. By using the LUCC three-level classification system in conjunction with ArcGIS 10.6 software, this study extracted the overall vegetation cover status in the Jiamusi area. This combination not only allows for the differentiation of specific land cover categories but also enables a continuous monitoring approach, providing a reliable and robust method. Previous studies, such as those by Andres [36] and Zhao [37], have used

this approach to obtain highly accurate results in vegetation distribution, demonstrating its effectiveness in different landscapes and validating its scientific soundness in this context.

The analysis of the extracted vegetation cover data shows that the vegetation coverage in the Jiamusi area has shown a significant downward trend in the past 20 years, which is similar to the results of Feng [38] and Zhang [39]. This means that the current vegetation coverage in northern China is under threat. According to data from the National Bureau of Statistics, the grassland area in the northeast region has been decreasing since 2000, which is closely related to local land degradation and overcultivation [40]. Gao et al. [40] and Tian et al. [41] studied the vegetation changes in the northeast region and found that the direct cause of vegetation loss was the change in land use, with most of the area being occupied by cultivated land and building land. Samaneh et al.'s [42] study on urbanization in southern Europe indicates that increased human pressure reduces vegetation cover, decreases plant density and diversity, and alters species composition, thus limiting the ability of nature to provide important ecosystem services. At the same time, vegetation in other parts of the world has been seriously threatened over the past few decades as a result of human activities and natural disasters [43]. The study found that the vegetation coverage in Jiamusi City showed a decreasing trend from 2000 to 2020. Among them, Fuyuan City and Tongjiang City showed a more significant decline in vegetation coverage, which may be more influenced by local urban development and expansion of cultivated land. It is easy to see from Figure 5 that the construction land area in Jiamusi City has been steadily increasing since 2000. Considering that there has been little change in vegetation cover in the counties along the Songhua River since 2000, it is speculated that this phenomenon may be closely related to the development of agriculture and other industries in the area. According to the spatial analysis, although there was a decrease in vegetation cover, the concentration of vegetation in the urban core areas has increased, whereas the vegetation in the surrounding areas is showing a trend towards fragmentation. This is in line with previous studies conducted in the northeastern region [44–46]. In addition, studies from other regions have also found similar trends. For instance, research by Harini [47] revealed significant differences in vegetation cover between the core and peripheral areas of Bangalore, a rapidly urbanizing city in southern India. The core area has been relatively well protected due to its historical development pattern, while the surrounding areas have experienced rapid deforestation and fragmentation. Bindajam et al.'s [48] study on the city of Maldah in India also supports this observation, noting an intensification of vegetation fragmentation in isolated areas surrounding rapidly urbanizing regions.

The results of the Geodetector analysis in this study indicate that both natural and human factors have some influence on vegetation coverage [49]. Natural factors are mainly manifested through climate change, temperature, and precipitation [50,51]. Guo et al. [52] investigated the effects of climate change on vegetation in the Sanjiangyuan area and found that vegetation stability is vulnerable to the effects of climate change, especially when temperature and rainfall increase, resulting in a gradual increase in vegetation cover. However, as temperatures decrease, vegetation cover also decreases. Loh et al. [53] also studied the Sudan South Harbor area and concluded that with the decrease in rainfall and significant increase in temperature, the local vegetation may face potential threats in the future. Li et al. [54], through the analysis of vegetation changes in China's 400 mm annual precipitation fluctuation band from 1982 to 2018, found that climate change, especially changes in precipitation and temperature, has had a significant driving effect on vegetation activity. In this study, natural factors such as temperature, rainfall, and altitude were quantified and the contribution of natural factors to the detector results was relatively small. The q-values for AAT and AAP were 0.13669 and 0.1021, respectively, indicating that the impact of climate change on vegetation coverage change in the Jiamusi area is relatively weak. Furthermore, according to the meteorological data, the temperature in the Jiamusi area has increased by 0.9 degrees Celsius and precipitation has increased by 21% in the last 20 years, indicating a warming and wetter trend. However, vegetation coverage in the Jiamusi area continues to decline, indicating that the positive impact of climate change

on local vegetation coverage is relatively small compared to human factors. In recent years, the current and expected impacts of climate warming on vegetation cover have been widely studied, and some researchers believe that climate change has a significant impact on vegetation cover, and it is urgent to determine the key meteorological factors affecting vegetation cover changes [55]. However, Liu et al. [56], in their study of vegetation cover in the Poyang Lake Basin, concluded that both climatic factors and human activities affect the vegetation cover rate, but significant changes in vegetation cover are caused by human activities.

Some researchers argue that the relationship between socio-economic development and vegetation cover is more complex than the obvious effects of climate change [25]. In addition, changes in land use and land cover, particularly human-induced habitat destruction, exacerbate the ecological vulnerability of vegetation [57]. For instance, Zhang et al. [58] found that surface soil and vegetation were destroyed by open-pit mining in the Pingluo area of Shanxi, resulting in a decrease in vegetation cover. Jian et al. [59] concluded that human activities are gradually dominating vegetation changes. Similarly, Liu et al. [60] analyzed human-induced land use changes in the Yellow River Basin and found that the expansion of agricultural land and land degradation have reduced the area of natural vegetation, which is unfavorable for the stability and protection of the original ecosystem functions of vegetation. This study also examined the relationship between human activities and vegetation coverage. It was observed that the dominant factors causing vegetation changes during the study period were the expansion of CL areas and the encroachment of DF on VCL. The interaction between natural factors and human activities has also been discussed. In this study, the interaction between these two factors mainly showed a nonlinear enhancement, indicating that the vegetation coverage change is the result of the comprehensive action of various factors. As shown in Figure 6, the interaction between CL and all other factors was significant. Combined with the variability and growth of land use contributions in Geodetector and the acceleration of urbanization, it is clear that human activity is the dominant factor affecting vegetation coverage changes. The results of this study suggest that human activities may have a greater impact on future vegetation coverage and that there is still a risk of further vegetation degradation in the Jiamusi area.

Since this study is based on remote sensing image extraction for vegetation coverage change analysis, there may be some errors due to limitations in remote sensing image quality and algorithms. In the future, we will use higher-resolution remote sensing images to extract vegetation coverage data. In addition, vegetation coverage change is influenced by many factors. The influencing factors selected in this study are not comprehensive and do not consider other factors that affect changes in vegetation coverage distribution, such as vegetation type, moisture, soil type, and soil salinity. These other factors should be considered in future research. Despite these limitations, this study predicted future land use changes and effectively quantified the relative contributions of different drivers of vegetation coverage. The study showed that both natural and human factors influence vegetation coverage, but human factors still dominated.

5. Conclusions

Based on the remote sensing data from 2000 to 2020 and the Geodetector model, the effects of natural factors and human activities on vegetation coverage in Jiamusi City were quantitatively analyzed. The main conclusions were as follows:

(1) In the past two decades, the vegetation coverage in Jiamusi City, China, has significantly shrunk. This reduction can be attributed to land degradation, intensified farming, and changes in land use patterns. The spatial distribution of vegetation cover in the urban core area has become more concentrated, while the fragmentation in the surrounding areas has intensified.

(2) The results of the Geodetector analysis indicate that climate change, temperature, and precipitation in Jiamusi City have some impact on vegetation coverage, but compared to the influence of human activities, these natural factors play a relatively smaller role.

In particular, changes in land use, habitat destruction caused by human activities, and the expansion of construction land have had a significant impact on the reduction of vegetation coverage.

(3) Compared to other similar studies, this research had a specific focus on the Jiamusi region. While these results provide a unique perspective on specific phenomena in this area, they do not constitute a groundbreaking contribution. Rather, they can be seen as a piece of a broader research puzzle, aligning with other studies and providing additional context and understanding for the field. This approach not only promotes a more comprehensive understanding of vegetation coverage changes but also offers important references for future ecological conservation and land use policies.

Author Contributions: Conceptualization, M.W., Y.W. and Z.L.; methodology, M.W. and Y.W.; validation, M.W., Y.W., Z.L. and H.Z.; formal analysis, M.W. and H.Z.; investigation, Z.L.; writing—original draft preparation, M.W.; writing—review and editing, M.W., Y.W. and Z.L.; supervision, Z.L. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Data Availability Statement: The information used in the analysis is accessible from the public data sources.

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

References

1. Li, J.; Wang, J.L.; Zhang, J.; Liu, C.L.; He, S.L.; Liu, L.F. Growing-season vegetation coverage patterns and driving factors in the China-Myanmar Economic Corridor based on Google Earth Engine and geographic detector. *Ecol. Indic.* **2022**, *136*, 108620. [CrossRef]
2. Li, J.; Wang, J.L.; Zhang, J.; Zhang, J.P.; Kong, H. Dynamic changes of vegetation coverage in China-Myanmar economic corridor over the past 20 years. *Int. J. Appl. Earth Obs. Geoinf.* **2021**, *102*, 102378. [CrossRef]
3. Yao, R.; Cao, J.; Wang, L.C.; Zhang, W.W.; Wu, X.J. Urbanization effects on vegetation cover in major African cities during 2001–2017. *Int. J. Appl. Earth Obs. Geoinf.* **2019**, *75*, 44–53. [CrossRef]
4. Myeong, S.; Nowak, D.J.; Duggin, M.J. A temporal analysis of urban forest carbon storage using remote sensing. *Remote Sens. Environ.* **2006**, *101*, 277–282. [CrossRef]
5. Zhang, B.; Yang, Y.-S.; Zepp, H. Effect of vegetation restoration on soil and water erosion and nutrient losses of a severely eroded clayey Plinthudult in southeastern China. *CATENA* **2004**, *57*, 77–90. [CrossRef]
6. Fang, C.-F.; Ling, D.-L. Investigation of the noise reduction provided by tree belts. *Landsc. Urban Plan.* **2003**, *63*, 187–195. [CrossRef]
7. Wang, Z.R.; Niu, D.C.; Hu, Y.G.; Wang, Y.S.; Huang, L.; Liu, Y.B. Changes in soil phosphorus fractions associated with altered vegetation and edaphic conditions across a chronosequSence of revegetated dunes in a desert area. *Geoderma* **2022**, *424*, 115995. [CrossRef]
8. Linden, J.; Gustafsson, M.; Uddling, J.; Watne, A.; Pleijel, H. Air pollution removal through deposition on urban vegetation: The importance of vegetation characteristics. *Urban For. Urban Green.* **2023**, *81*, 127843. [CrossRef]
9. Cai, M.; Xin, Z.; Yu, X. Spatio-temporal variations in PM leaf deposition: A meta-analysis. *Environ. Pollut.* **2017**, *231*, 207–218. [CrossRef]
10. Megahed, Y.; Cabral, P.; Silva, J.; Caetano, M. Land Cover Mapping Analysis and Urban Growth Modelling Using Remote Sensing Techniques in Greater Cairo Region-Egypt. *ISPRS Int. J. Geo-Inf.* **2015**, *4*, 1750–1769. [CrossRef]
11. Kong, Z.; Ling, H.; Deng, M.; Han, F.; Yan, J.; Deng, X.; Wang, Z.; Ma, Y.; Wang, W. Past and projected future patterns of fractional vegetation coverage in China. *Sci. Total Environ.* **2023**, *902*, 166133. [CrossRef] [PubMed]
12. Zuo, Y.F.; Li, Y.H.; He, K.N.; Wen, Y.S. Temporal and spatial variation characteristics of vegetation coverage and quantitative analysis of its potential driving forces in the Qilian Mountains, China, 2000–2020. *Ecol. Indic.* **2022**, *143*, 109429. [CrossRef]
13. Zhu, J.; Zhu, C.; Lu, D.; Wang, G.G.; Zheng, X.; Cao, J.; Zhang, J. Regeneration and succession: A 50-year gap dynamic in temperate secondary forests, Northeast China. *For. Ecol. Manag.* **2021**, *484*, 118943. [CrossRef]
14. Gu, Z.; Duan, X.; Shi, Y.; Li, Y.; Pan, X. Spatiotemporal variation in vegetation coverage and its response to climatic factors in the Red River Basin, China. *Ecol. Indic.* **2018**, *93*, 54–64. [CrossRef]
15. Piao, S.; Cui, M.; Chen, A.; Wang, X.; Ciais, P.; Liu, J.; Tang, Y. Altitude and temperature dependence of change in the spring vegetation green-up date from 1982 to 2006 in the Qinghai-Xizang Plateau. *Agric. For. Meteorol.* **2011**, *151*, 1599–1608. [CrossRef]
16. Sun, H.; Wang, C.; Niu, Z. Analysis of the Vegetation Cover Change and the Relationship between NDVI and Environmental Factors by Using NOAA Time Series Data. *J. Remote Sens.* **1998**, *266*, 153–161.

17. Dong, Q.M.; Zhao, X.Q.; Wu, G.L.; Shi, J.J.; Ren, G.H. A review of formation mechanism and restoration measures of "black-soil-type" degraded grassland in the Qinghai-Tibetan Plateau. *Environ. Earth Sci.* **2013**, *70*, 2359–2370. [CrossRef]
18. He, H.S.; Hao, Z.; Mladenoff, D.J.; Shao, G.; Hu, Y.; Chang, Y. Simulating forest ecosystem response to climate warming incorporating spatial effects in north-eastern China. *J. Biogeogr.* **2005**, *32*, 2043–2056. [CrossRef]
19. Li, G.Q.; Bai, F.; Sang, W.G. Different responses of radial growth to climate warming in Pinus koraiensis and Picea jezoensis var. komarovii at their upper elevational limits in Changbai Mountain, China. *Chin. J. Plant Ecol.* **2011**, *35*, 500–511. [CrossRef]
20. Chen, Q.; Zhou, Q.; Zhang, H.F.; Liu, F.G. Spatial disparity of NDVI response in vegetation growing season to climate change in the Three-River Headwaters Region. *Ecol. Environ. Sci.* **2010**, *19*, 1284–1289.
21. Sun, R.; Liu, C.M.; Zhu, Q.J. Relationship Between the Fractional Vegetation Cover Change and Rainfall in the Yellow River Basin. *Acta Geogr. Sin.* **2001**, *56*, 672–680.
22. Wang, Y.; Chen, X.; Gao, M.; Dong, J. The use of random forest to identify climate and human interference on vegetation coverage changes in southwest China. *Ecol. Indic.* **2022**, *144*, 109463. [CrossRef]
23. Zhuang, L.; Axmacher, J.C.; Sang, W. Different radial growth responses to climate warming by two dominant tree species at their upper altitudinal limit on Changbai Mountain. *J. For. Res.* **2017**, *28*, 795–804. [CrossRef]
24. Hao, J.; Xu, G.; Luo, L.; Zhang, Z.; Li, H. Quantifying the relative contribution of natural and human factors to vegetation coverage variation in coastal wetlands in China. *CATENA* **2020**, *188*, 104429. [CrossRef]
25. Yang, S.; Song, S.; Li, F.; Yu, M.; Yu, G.; Zhang, Q.; Cui, H.; Wang, R.; Wu, Y. Vegetation coverage changes driven by a combination of climate change and human activities in Ethiopia, 2003–2018. *Ecol. Inform.* **2022**, *71*, 101776. [CrossRef]
26. Wang, Y.M.; Zhang, Z.X.; Chen, X. Quantifying Influences of Natural and Anthropogenic Factors on Vegetation Changes Based on Geodetector: A Case Study in the Poyang Lake Basin, China. *Remote Sens.* **2021**, *13*, 5081. [CrossRef]
27. Ren, D.; Envelope, A.C.P. Analysis of the heterogeneity of landscape risk evolution and driving factors based on a combined GeoDa and Geodetector model. *Ecol. Indic.* **2022**, *144*, 109568. [CrossRef]
28. Zhai, H.; Lv, C.; Liu, W.; Yang, C.; Fan, D.; Wang, Z.; Guan, Q. Understanding Spatio-Temporal Patterns of Land Use/Land Cover Change under Urbanization in Wuhan, China, 2000–2019. *Remote Sens.* **2021**, *13*, 3331. [CrossRef]
29. Long, X.; Lin, H.; An, X.; Chen, S.; Qi, S.; Zhang, M. Evaluation and analysis of ecosystem service value based on land use/cover change in Dongting Lake wetland. *Ecol. Indic.* **2022**, *136*, 108619. [CrossRef]
30. Qiao, Y.; Wang, X.; Han, Z.; Tian, M.; Wang, Q.; Wu, H.; Liu, F. Geodetector based identification of influencing factors on spatial distribution patterns of heavy metals in soil: A case in the upper reaches of the Yangtze River, China. *Appl. Geochem.* **2022**, *146*, 105459. [CrossRef]
31. Wang, J.; Xu, C. Geodetector: Principle and prospective. *Acta Geogr. Sin.* **2017**, *72*, 116–134.
32. Chen, S.T.; Guo, B.; Zhang, R.; Zang, W.Q.; Wei, C.X.; Wu, H.W.; Yang, X.; Zhen, X.Y.; Li, X.; Zhang, D.F.; et al. Quantitatively determine the dominant driving factors of the spatial-temporal changes of vegetation NPP in the Hengduan Mountain area during 2000–2015. *J. Mt. Sci.* **2021**, *18*, 427–445. [CrossRef]
33. Xie, Y.; Sha, Z.; Yu, M. Remote sensing imagery in vegetation mapping: A review. *J. Plant Ecol.* **2008**, *1*, 9–23. [CrossRef]
34. Valjarević, A.; Djekić, T.; Stevanović, V.; Ivanović, R.; Jandziković, B. GIS numerical and remote sensing analyses of forest changes in the Toplica region for the period of 1953–2013. *Appl. Geogr.* **2018**, *92*, 131–139. [CrossRef]
35. Wang, Y.F.; Tan, L.; Wang, G.Y.; Sun, X.Y.; Xu, Y.N. Study on the Impact of Spatial Resolution on Fractional Vegetation Cover Extraction with Single-Scene and Time-Series Remote Sensing Data. *Remote Sens.* **2022**, *14*, 4165. [CrossRef]
36. Andres, S.; Adrian, F.; Graciela, M. Assessing the Accuracy of Landsat Vegetation Fractional Cover for Monitoring Australian Drylands. *Remote Sens.* **2022**, *14*, 6322.
37. Zhao, H.; He, H.; Wang, J.; Bai, C.; Zhang, C. Vegetation Restoration and Its Environmental Effects on the Loess Plateau. *Sustainability* **2018**, *10*, 4676. [CrossRef]
38. Feng, L.L.; Jia, Z.Q.; Li, Q.X.; Zhao, A.Z.; Zhao, Y.L.; Zhang, Z.J. Spatiotemporal Change of Sparse Vegetation Coverage in Northern China. *J. Indian Soc. Remote Sens.* **2019**, *47*, 359–366. [CrossRef]
39. Zhang, L.J.; Li, W.L.; Jiang, C.Y.; Zang, S.Y. Examining the century dynamic change of forest oxygen production in Heilongjiang Province, China. *Int. J. Environ. Sci. Technol.* **2015**, *12*, 4005–4016. [CrossRef]
40. Gao, J.; Liu, Y. Determination of land degradation causes in Tongyu County, Northeast China via land cover change detection. *Int. J. Appl. Earth Obs. Geoinf.* **2010**, *12*, 9–16. [CrossRef]
41. Tian, J.; Wang, B.; Zhang, C.; Li, W.; Wang, S. Mechanism of regional land use transition in underdeveloped areas of China: A case study of northeast China. *Land Use Policy* **2020**, *94*, 104538. [CrossRef]
42. Seifollahi-Aghmiuni, S.; Kalantari, Z.; Egidi, G.; Gaburova, L.; Salvati, L. Urbanisation-driven land degradation and socioeconomic challenges in peri-urban areas: Insights from Southern Europe. *Ambio* **2022**, *51*, 1446–1458. [CrossRef] [PubMed]
43. Ranjan, A.K.; Gorai, A.K. Characterization of vegetation dynamics using MODIS satellite products over stone-mining dominated Rajmahal Hills in Jharkhand, India. *Remote Sens. Appl. Soc. Environ.* **2022**, *27*, 100802. [CrossRef]
44. Ma, X.; Geng, Y.; Chen, X. Niche evaluation and evolution path selection of forestry enterprises in Northeast state-owned forest region. *Glob. Nest J.* **2020**, *22*, 511–521.
45. Zhang, X.; Wang, W.C.; Fang, X.; Ye, Y.; Zheng, J. Vegetation of Northeast China during the late seventeenth to early twentieth century as revealed by historical documents. *Reg. Environ. Chang.* **2011**, *11*, 869–882. [CrossRef]

46. Liu, D.; Wang, Z.; Song, K.; Zhang, B.; Hu, L.; Huang, N.; Zhang, S.; Luo, L.; Zhang, C.; Jiang, G. Land use/cover changes and environmental consequences in Songnen Plain, Northeast China. *Chin. Geogr. Sci. Engl.* **2009**, *19*, 299–305. [CrossRef]
47. Nagendra, H.; Nagendran, S.; Paul, S.; Pareeth, S. Graying, greening and fragmentation in the rapidly expanding Indian city of Bangalore. *Landsc. Urban Plan.* **2012**, *105*, 400–406. [CrossRef]
48. Bindajam, A.A.; Mallick, J.; Hang, H.T. Assessing landscape fragmentation due to urbanization in English Bazar Municipality, Malda, India, using landscape metrics. *Environ. Sci. Pollut. Res.* **2023**, *30*, 68716–68731. [CrossRef]
49. Wu, H.F.; Zhang, J.Y.; Bao, Z.X.; Wang, G.Q.; Wang, W.S.; Yang, Y.Q.; Wang, J.; Kan, G.Y. The impacts of natural and anthropogenic factors on vegetation change in the Yellow-Huai-Hai River Basin. *Front. Earth Sci.* **2022**, *10*, 959403. [CrossRef]
50. Jing, X.; Yao, W.Q.; Wang, J.H.; Song, X.Y. A study on the relationship between dynamic change of vegetation coverage and precipitation in Beijing's mountainous areas during the last 20 years. *Math. Comput. Model. Int. J.* **2011**, *54*, 1079–1085. [CrossRef]
51. Chen, M.H.; Zeng, S.D.; Jiang, B.; Wen, Z.F.; Wu, J.; Xia, J. The comprehensive evaluation of how water level fluctuation and temperature change affect vegetation cover variations at a lake of ecological importance (Poyang Lake), China. *Ecol. Indic.* **2023**, *148*, 110041. [CrossRef]
52. Guo, B.; Wang, J.; Mantravadi, V.S.; Zhang, L.; Liu, G. Effect of climate and ecological restoration on vegetation changes in the "Three-River Headwaters" region based on remote sensing technology. *Environ. Sci. Pollut. Res.* **2022**, *29*, 16436–16448. [CrossRef] [PubMed]
53. Loh, P.S.; Alnoor, I.M.; He, S. Impact of Climate Change on Vegetation Cover at South Port Sudan Area. *Climate* **2020**, *8*, 114. [CrossRef]
54. Li, Y.; Zheng, Z.; Qin, Y.; Rong, P. Relative contributions of natural and man-made factors to vegetation cover change of environmentally sensitive and vulnerable areas of China. *J. Clean. Prod.* **2021**, *321*, 128917. [CrossRef]
55. Bai, H.; Li, L.; Wu, Y.; Feng, G.; Gong, Z.; Sun, G. Identifying Critical Meteorological elements for vegetation coverage change in China. *Front. Phys.* **2022**, *10*, 3. [CrossRef]
56. Liu, H.; Zheng, L.; Liao, M. Dynamics of Vegetation Change and Its Relationship with Nature and Human Activities—A Case Study of Poyang Lake Basin, China. *J. Sustain. For.* **2020**, *40*, 47–67. [CrossRef]
57. Li, J.; Peng, S.; Li, Z. Detecting and attributing vegetation changes on China's Loess Plateau. *Agric. For. Meteorol.* **2017**, *247*, 260–270. [CrossRef]
58. Zhang, M.; Wang, J.M.; Li, S.J. Tempo-spatial changes and main anthropogenic influence factors of vegetation fractional coverage in a large-scale opencast coal mine area from 1992 to 2015. *J. Clean. Prod.* **2019**, *232*, 940–952. [CrossRef]
59. Jian, S.Q.; Zhang, Q.K.; Wang, H.L. Spatial-Temporal Trends in and Attribution Analysis of Vegetation Change in the Yellow River Basin, China. *Remote Sens.* **2022**, *14*, 4607. [CrossRef]
60. Liu, B.; Pan, L.B.; Qi, Y.; Guan, X.; Li, J.S. Land Use and Land Cover Change in the Yellow River Basin from 1980 to 2015 and Its Impact on the Ecosystem Services. *Land* **2021**, *10*, 1080. [CrossRef]

Disclaimer/Publisher's Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.