

Article

Carbon Emission Effects of Land Use in Chaobai River Region of Beijing–Tianjin–Hebei, China

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Abstract: Beijing–Tianjin–Hebei, the main economic area in northern China, has seen significant changes in its regional economic and physical landscape as a result of the coordinated development strategy. Assessing the link between land use and land cover (LULC) change and carbon emissions in the Chaobai River region, which represents the growth of the Beijing–Tianjin–Hebei urban agglomeration, is crucial to achieve coordinated low-carbon development in this area. This study uses statistics from statistical yearbooks of Chinese provinces and cities along with land use change data to analyze the relationship between land use changes and carbon emissions in the Chaobai River region from 2001 to 2017 using dynamic land use attitudes and land use transfer matrices, combined with carbon emission factors based on the IPCC inventory method and carbon emission models for energy consumption. In addition, this study makes use of the LMDI model and geographical detectors to identify and assess the factors that influence changes in land use carbon emissions and the driving forces behind the regional differentiation of land use changes. The results show that: (1) The Chaobai River region’s predominant land use classes during the past 17 years have been agricultural land and construction land. In addition to the decrease in cropland and the increase in urban land, the land use patterns of other land classes also changed to a certain extent. (2) Carbon emissions from land use showed an increasing trend, from 6.1×10^6 tons in 2001 to 1.1×10^7 tons in 2017. (3) Carbon emission intensity, economic development level, land use efficiency, and construction land scale have a certain regularity in the evolution of carbon emissions, and economic development level has become the most important driving factor controlling the growth of land use carbon emissions. (4) Driving factors in different periods have different degrees of influence on land use change, among which socio-economic factors such as population density and GDP have the strongest explanatory power. In addition, the interactions of each factor mainly present a double factor enhancement. In the future, the Chaobai River region should be based on the coordinated development strategy and take the “double carbon” target as its guiding principle to promote the innovation of the regional development system and further achieve the optimization of the regional land use patterns.

Keywords: land use; carbon emission; LMDI; geographical detectors; the Chaobai River region



Citation: Liu, C.; Xu, R.; Xu, K.; Lin, Y.; Cao, Y. Carbon Emission Effects of Land Use in Chaobai River Region of Beijing–Tianjin–Hebei, China. *Land* **2023**, *12*, 1168. <https://doi.org/10.3390/land12061168>

Academic Editors: Xue-Chao Wang, Weize Song, Yingjie Li and Marko Scholze

Received: 5 April 2023

Revised: 20 May 2023

Accepted: 30 May 2023

Published: 1 June 2023



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1. Introduction

According to the CO₂.earth [<https://www.co2.earth/>] (accessed on 10 October 2022), China now has the second-highest historical cumulative energy consumption and CO₂ emissions in the world, after the United States, and it is predicted that China’s emissions will surpass those of the United States by 2025. As a result, China must urgently regulate CO₂ emissions [1,2]. Carbon peaking and carbon neutrality are the two components of the “double carbon” target. Carbon peaking describes a peak in carbon dioxide emissions followed by a gradual decline, and carbon neutrality refers to actions that humans take to offset their own greenhouse gas emissions through afforestation, energy conservation and emission reduction, ultimately achieving zero carbon dioxide emissions [3]. At the US–China Joint Statement on Climate Change in 2014, China made the initial proposal to

reach carbon peaking by 2030. China once more proposed a “double carbon” aim to achieve carbon peaking by 2030 and carbon neutrality by 2060 during the UN General Assembly in September 2020 [4]. In addition to reflecting China’s status as a great power, the adoption of the “double carbon” target is a significant strategic move taken by China to further sustainable human growth [5,6]. Land is a carrier of resources and environmental factors. LULC reflects the dual natural and social attributes contained in land under the effect of human activities. By altering how land is utilized and maintained, humans can better satisfy their own development goals [7,8]. Numerous recent studies have indicated that LULC is the second most significant factor influencing changes in global carbon emissions after fossil fuel combustion [9,10]. An organic relationship between carbon emissions and land can be established through the dual roles of carbon source and sink, with the help of the land use class conversion mechanism and the land use class maintenance mechanism. In order to accomplish the green and low-carbon development of the Beijing–Tianjin–Hebei urban agglomeration and to promote the sustainable development of the region, it is crucial to study land use change and its implications for carbon emissions from the perspective of LULC.

Researchers from different countries began studying land use and terrestrial carbon cycle systems as early as the 1970s in an effort to clarify the relationship between the two and fully utilize the dynamic role of land as a carrier of social and economic activities in social production and nation building. This field is best exemplified by the research of Professor Houghton [11–13], who summarized and analyzed the existing methods and problems of LULC and net carbon flux measurement. The bookkeeping model he established was used for global carbon stock and carbon intensity changes due to LULC. He mentioned that people should pay attention to the changes brought about by different land management methods. Fang, Jing-Yun and Park, Se-Long [14,15], addressing the “lost sink puzzle”, suggested that terrestrial ecosystems in the Northern Hemisphere represent a significant carbon sink, and they claimed that the role of the soil cycle should be emphasized to reduce the uncertainty in carbon sink estimates. Chen Guangsheng et al. [16] argued that global LULC has strong spatial variability and the impact of ecosystems on the carbon cycle also has obvious geographical disparities. Since land use carbon emissions are affected by both highly uncertain natural ecological processes and complex socio-economic activities, a unified method of accounting for land use carbon emissions has not yet been developed. At present, the commonly used method of carbon accounting is mainly based on the greenhouse gas inventory method, i.e., according to the Inter-governmental Panel on Climate Change 2006 guidelines [17], or the accounting categories are determined by each country and region to account for greenhouse gas emissions. Meanwhile, studies on carbon emissions based on the greenhouse gas inventory approach are gradually increasing, such as carbon footprint studies. Other widely used measurement methods include vorticity correlation methods, modeling methods (such as bookkeeping and scenario analysis models), and remote sensing satellite methods [18–21]. Houghton et al. have summarized the methods used to estimate carbon density and changes in carbon density due to LULC. They include inventory-based carbon density estimation, accounting models that track changes in carbon pools and satellite-based carbon density estimation methods [22]. Based on extensive reference to relevant research results from various countries, Fang Jingyun et al. estimated the carbon sink of terrestrial vegetation in China from 1981 to 2000 using forest and grassland resource inventory data, climate and other ground observation data and satellite remote sensing data [23]. Their research gave researchers a theoretical foundation for future research on carbon emissions in various Chinese locations. The depth of study on the various elements and routes of carbon emissions from land use has been greatly enhanced by scholars from many different countries.

Located in the heart of China’s Bohai Sea Rim, Beijing–Tianjin–Hebei is the largest and most vibrant economic region in northern China. With the rapid urbanization process, the tension between the lack of available land and the growing demand for land has become more obvious. Numerous ecological areas which are located in the inner and peripheral

parts of the cities, including forest, grassland and waters, are being continually encroached upon, which is causing increasingly significant environmental issues such as water contamination and a dramatic fall in biodiversity [24]. With the steady advancement of ecological civilization and the ongoing promotion of the coordinated development strategy, the land use structure of Beijing–Tianjin–Hebei is being optimized. The theoretical system and mechanism of the driving force of land change have become more intricate. The Chaobai River is situated in the Beijing–Tianjin–Hebei border region. As the ecological barrier to the Beijing–Tianjin–Hebei urban agglomeration, it is the epitome of the coordinated development strategy. It is undergoing drastic changes in land use patterns due to a combination of factors such as urban construction, industrial park construction and traffic development. In order to rationalize regional land use, promote low carbon synergistic development of the region and advance the development of ecological civilization, it is crucial to study land use change and the impact of land use change on carbon emissions in the Chaobai River region. Additionally, current research by scholars from various countries has focused on vast geographic areas such as cities or entire nations. In contrast to the previous conventional site selection criteria above, this research focuses on the ecological functions of river flows in urban environments. It can provide guidance for urban development from a new perspective.

Based on land use change data, this research uses the land use dynamics and land use transfer matrix to analyze the pattern of land use change in the Chaobai River region between 2001 and 2017. Following that, we use carbon emission factors based on the IPCC inventory method and carbon emission models for energy consumption to calculate the net land use carbon emissions by using data on social, economic and energy consumption variables. The cumulative effects and cumulative contribution of each influencing factor on the change in land use carbon emissions are then calculated and examined using the LMDI model. Finally, the study uses the geographical detector to analyze the intrinsic drivers of regional land use change. It is anticipated to serve as a reference for sustainable land use and optimization of land use patterns in the Chaobai River region and to provide a boost to the realization of regional human–land coordination and low-carbon development.

2. Materials and Methods

2.1. Overview of the Study Area

The Chaobai River flows through the three provinces (cities) of Beijing, Tianjin and Hebei in the northern part of the North China Plain and is one of the five main rivers in the Haihe River system.

This study focuses on the key areas of the Chaobai River in the Beijing–Tianjin–Hebei region, namely Tongzhou and Shunyi districts in Beijing, Baodi district in Tianjin and Sanhe, Dachang and Xianghe counties in Hebei (see Figure 1). These six counties and cities, which are closely spatially connected, are the main flow areas of the Chaobai River in the Beijing–Tianjin–Hebei region, and they are the important connecting point of the Beijing–Tianjin–Hebei city cluster.

2.2. Data Sources

The energy consumption data of coal, coke, crude oil, etc. used in this study were obtained from the 2001, 2005, 2009, 2013 and 2017 statistical yearbooks of Beijing and Tianjin, the 2001, 2005, 2009, 2013 and 2017 economic yearbooks, as well as data on the administrative divisions and regional development status of each district and county, etc. The standard coal conversion coefficient and carbon emission coefficient of energy was obtained from China Energy Statistics Year and IPCC (2006) [17]. Night light data and GDP data were obtained from the Resource and Environmental Science and Data Center of the Chinese Academy of Sciences [<https://www.resdc.cn> (accessed on 23 October 2022)]. The land use change data were obtained from the Geospatial Data Cloud [<http://www.gscloud.cn/> (accessed on 25 October 2022)], which is a remote interpretation of Landsat remote sensing image maps from 2001 to 2017, with an accuracy of 30 m. The

classification of land use data is based on the Second National Land Survey and with reference to the classification methods in relevant literature. The land classes in the study area were divided into seven primary classes, namely cropland, forest, grassland, urban land, rural settlements, industrial and mining land and waters. Remote sensing monitoring (ENVI ver. 4.2, California, United States) and geographic information systems (ArcMap ver. 10.3, California, United States) were used. The five phases of land use remote sensing data of the Beijing–Tianjin–Hebei region in 2001, 2005, 2009, 2013 and 2017 and the boundary vector files of Tongzhou and Shunyi districts in Beijing, Baodi district in Tianjin, Sanhe, Dachang and Xianghe counties in Hebei were used to merge and crop the land categories to obtain the five phases of land use data of the study area (see Figure 2).

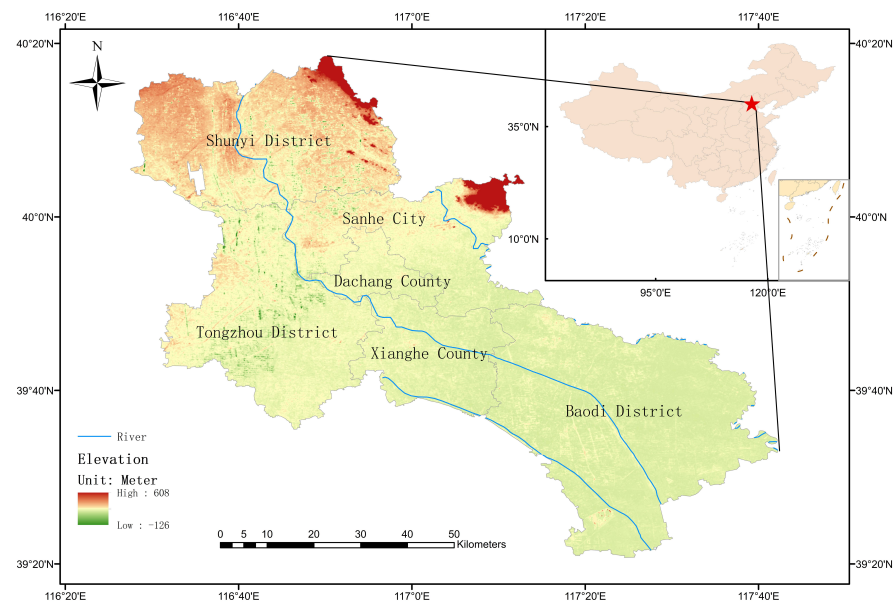


Figure 1. Location of the study area.

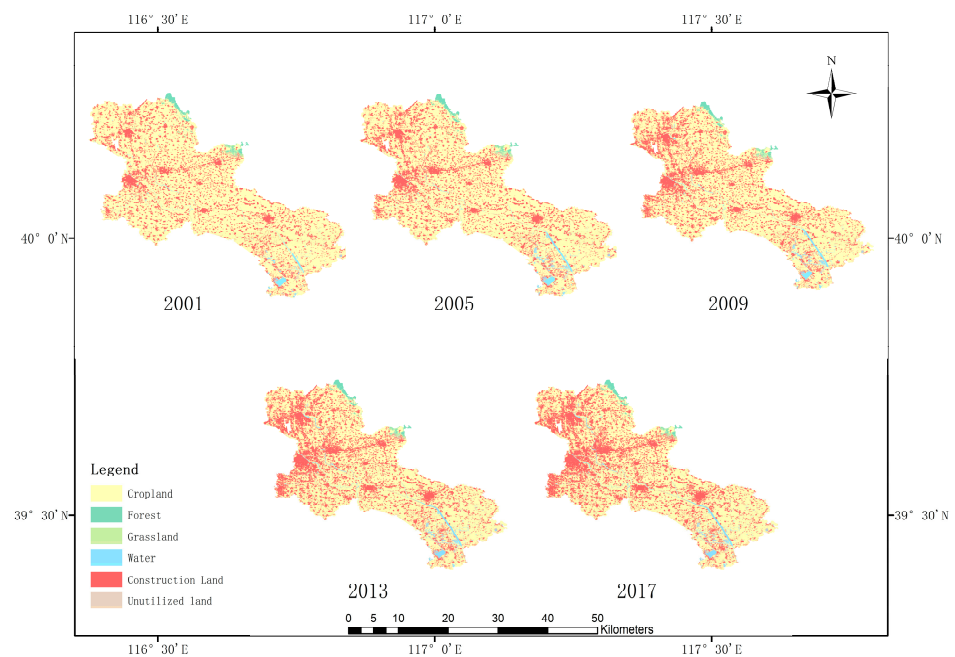


Figure 2. The land use map in the Chaobai River region from 2001 to 2017.

2.3. Method

2.3.1. Land Use Dynamics

The single land use dynamic can reflect the dynamic changes in different land use classes in the study area during a specific time period. It can visually reflect the area change in a land use class and the sharpness of the rate change during the study period. This result can reflect the impact of human activities on land use in the region and thus better guide the land use in the area [25].

The formula is as below:

$$K = \frac{U_b - U_a}{U_a} \times \frac{1}{T} \times 100 \quad (1)$$

where K refers to the land use dynamic of a certain land use class in one study period with the unit of %. U_a and U_b refer to areas of certain land use classes at the beginning and the end of the study period, respectively, in km^2 . T refers to study time.

2.3.2. Land Use Transfer Matrix

The land use transfer matrix is an application of the Markov model to the field of land use change, which enables a two-dimensional matrix to be derived based on the relationship between changes in the current state of land cover in different time phases in the same area. It is followed by an analysis of the resulting transfer matrix to obtain two phases and to yield the interconversion of different land classes between the years [26–28].

The two-dimensional matrix describes the changes in land category, quantity and area of different land use classes in different years. It reflects the data on the area of each land use class and the flow in and out of each land use class in a given area during the corresponding period of the study, enabling the general trend in land use change and the change in land use structure to be understood [29].

2.3.3. Estimation of Land Use Carbon Emission

Since land use changes are influenced by a combination of natural factors such as topography, climate and soil, as well as anthropogenic factors such as economic conditions and social policies, leading to more uncertainties in the study of carbon emissions driven by its land use and its changes, and the methods of accounting for land use carbon emissions are still not unified [30]. However, numerous academics have already categorized and summarized the existing studies and come to the conclusion that the effects of current land use carbon emission include direct effects and indirect effects, which correspond to the effects on natural carbon processes and on anthropogenic carbon processes, respectively [31]. The direct effects are the changes in land use class and land management practices that have an impact on plant biomass, soil respiration rate and vegetation carbon sequestration efficiency. The indirect effects are primarily caused by regional carbon emissions driven by industrialization and urbanization, which affect the manner and intensity of human socio-economic activities and thus bring about regional carbon emissions. Current studies of carbon emissions from human activities carried out on different classes of land mainly rely on statistical data of human activities, such as energy activities, industrial processes, product usage and waste disposal. This is because, in recent decades, more than 70–90% of all anthropogenic carbon emissions have come from energy-related activities, industrial processes and product consumption, while the energy consumption intensity and carbon emission intensity of different land use classes such as forest, grassland and cropland in agricultural land, and commercial and industrial land in construction land are mostly the same [32,33]. Additionally, it is because construction land is the main land use type for carbon emissions from energy and industrial sources, and the majority of carbon emissions from energy and industrial sources occur on urban construction land, which is closely related to economic development and human life demand, industrial structure and other factors.

On the basis of this, a thorough model for estimating the carbon emissions from land use may be built to directly or indirectly estimate the carbon emissions from various land use classes. Since the carbon emissions of construction land cannot be estimated directly, this study measures it indirectly through the energy consumption carbon emission model. Based on production characteristics, different land use classes are classified into two categories: construction land and agricultural land. Among them, construction land includes urban residential land, industrial and mining land, transportation land, etc. Its land use pattern shows that construction land mainly participates in carbon emission accounting as a carbon source, and its role as a carbon sink is negligible. Based on the IPCC (2006) [17], the land use carbon emissions of construction land are estimated indirectly through the consumption of various energy sources, i.e., the carbon emissions from the production of energy consumed by the various activities undertaken by humans on it. The carbon emissions of construction land are calculated in terms of consumption of energy sources such as coal, coke, crude, oil, gas and electricity (see Table 1) [34,35].

Table 1. The conversion coefficient of energy (tc/tce).

Energy	Coal	Coke	Crude Oil	Gasoline	Kerosene	Diesel Oil	Fuel Oil	Natural Gas	Electricity
Standard Coal	0.7143	0.9714	1.43	1.4714	1.4714	1.4571	1.4286	1.3301	0.1229
Carbon Emission	0.7559	0.855	0.59	0.5538	0.5714	0.5921	0.6185	0.4483	0.7476

The formula is as below:

$$C = \sum C_i = \sum m_i \times j_i \times K_i \quad (2)$$

where C refers to the carbon emissions of construction land, in tons (t);

m_i refers to the i -th energy consumption, the unit of ton (t);

j_i refers to the i -th conversion coefficient of energy to standard coal;

K_i refers to carbon emission coefficient (tc/tce).

Since the study area is at the county and district scale, precise energy consumption data are not easily available. This study therefore refers to the method used in the existing literature to calculate the carbon emissions of construction land in districts and counties based on the energy consumption per unit of GDP [36,37]. The energy consumption per unit of GDP can indirectly yield the total energy consumption of each district and county, which is dominated by the energy consumption of construction land (see Table 2). Therefore, to a certain extent, the proportion of the total energy consumption of each district and county to the total energy consumption of the city reflects the carbon emissions of construction land in each district and county. Therefore, the carbon emissions of energy consumption in each district and county can be calculated indirectly.

Table 2. The energy consumption per unit GDP (tc/10⁴ RMB).

Year	Region	2001	2005	2009	2013	2017
	Beijing	1.51	0.986	0.543	0.358	0.264
	Tianjin	1.53	1.05	0.836	0.57	0.42
	Hebei	1.96	1.96	0.893	1.115	0.60

The formula is as below:

$$C_i = EI_i \times GDP_i \times Coe_{aver} = EI_i \times GDP_i \times \frac{C}{E} \quad (3)$$

where C refers to the total carbon emission of construction land, (Mt);

E refers to the total energy consumption, (Mt);

EI_i refers to the energy consumption per unit GDP of the i -th region, (tc/10⁴ RMB);
 $Co_{e_{aver}}$ refers to the average carbon emission coefficient of the energy (tc/tce).

The direct carbon emissions in this study refers to the carbon emissions from agricultural land. Agricultural land includes arable land, forests, grasslands and waters. The carbon emission factors for cropland, forest land, grassland, water and other land types are shown in Table 3 below. Due to the production activities such as tillage and fertilizer application, the carbon sink function of cropland is negligible compared to its carbon source function, so cropland counts as a carbon source, while forest, grassland and waters count as carbon sinks [38].

Table 3. Carbon emission (absorption) coefficient of each land use class (t/hm²).

Land Use Class	Cropland	Forest	Grassland	Waters	Others
Coefficient	0.422	−0.644	−0.020	−0.248	−0.005

The formula is as below:

$$C = \sum C_i = \sum T_i \times h_i \quad (4)$$

where C refers to the total carbon emissions of each land use class in tons (t);

C_i refers to the i -th class of land use in tons (t);

T_i refers to the i -th land use carbon emission coefficient, (t/hm²);

H_i refers to the i -th area of each land use class in hm².

2.3.4. LMDI Model

Currently, there are two main types of methods used to quantify decomposition changes in indicators: structural decomposition analysis (SDA) and index decomposition analysis (IDA). The SDA method requires input and output data as support. The IDA method requires only the use of departmental and aggregate data. It is particularly suitable for decomposing models that contain fewer factors and time series data, making it perfect for analyzing energy consumption and carbon emission drivers [39,40].

The IDA method can be further divided into two types: the Laspeyres index decomposition method and the Divisia index decomposition method, which mainly includes the arithmetic mean Divisia index method and the logarithmic mean Divisia index method (LMDI). Among them, the LMDI model has no unexplained residuals after decomposing the object and can use relatively simple conversion expressions for additive and multiplicative decomposition, so it is more commonly used in modelling the drivers of carbon emission factors [41].

In this study, four types of drivers, namely, carbon emission intensity, economic development level, land use efficiency and construction land scale were selected to create a decomposition model. The calculation formula is as follows:

$$C = \sum_i \frac{C_i}{GDP} \times \frac{GDP}{P} \times \frac{P}{S} \times S \quad (5)$$

where C refers to the total amount of land use carbon emission; C_i refers to the amount of carbon emission of a certain class of land; GDP refers to gross domestic product; P refers to the number of people in the region; S refers to the construction land area.

Let $A = \frac{C_i}{GDP}$, i.e., carbon emission per unit of GDP , characterizing the carbon emission intensity factor. $B = \frac{GDP}{P}$, i.e., GDP per capita, characterizing the economic development level factor. $D = \frac{P}{S}$, i.e., the number of people per unit of land area, characterizing the land use efficiency factor. $S = S$, i.e., the construction land area, characterizing the construction land scale factor.

Formula (5) can be rewritten as:

$$C = \sum_i C_i = \sum_i A_i \times B_i \times D \times S \quad (6)$$

Using the summation factor decomposition of the LMDI method, factor decomposition Equation (6) yields the following equation:

$$\Delta C_{t_0t} = C_t - C_0 = \Delta C_{Ai} + \Delta C_{Bi} + \Delta C_D + \Delta C_S \quad (7)$$

where ΔC_{t_0t} refers to CO₂ emission changes between 0 and t year. ΔC_{Ai} refers to the impact of carbon intensity on carbon emission. ΔC_{Bi} refers to the impact of economic development on carbon emission. ΔC_D refers to the impact of land use efficiency on carbon emission. ΔC_S refers to the impact of energy intensity of construction on carbon emission.

These formulas are as follows:

$$C_{Ai} = \sum_i A_i = \sum_i W_i \times \ln \frac{A_i^T}{A_i^0} \quad (8)$$

$$C_{Bi} = \sum_i B_i = \sum_i W_i \times \ln \frac{B_i^T}{B_i^0} \quad (9)$$

$$C_D = \sum_i D = \sum_i W_i \times \ln \frac{D^T}{D^0} \quad (10)$$

$$C_S = \sum_i S = \sum_i W_i \times \ln \frac{S^T}{S^0} \quad (11)$$

where $W_i = \frac{C^T - C^0}{\ln C^T - \ln C^0}$.

2.3.5. Geographical Detector

The geographical detector is a relatively new tool for exploring spatial variability based on spatial statistics, and its use as a powerful tool for driving force and factor analysis has been demonstrated in many cases in the natural and social sciences [42–45]. The geographical detectors can detect both numerical and qualitative data and consist of four detectors: variance and factor detection, interaction detection, risk detection and ecological detection [46–51]. In this study, the geographical detectors are used to explore the spatial heterogeneity of land use change in the Chaobai River region and the driving factors leading to the spatial heterogeneity are quantified, including factor detection and interaction detection.

(1) Factor detector

Detect the spatial heterogeneity of the dependent variable land use change Y , and obtain the extent to which a given driver X explains the spatial heterogeneity of the dependent variable land use change Y . This is measured by q values, whose expressions are:

$$q = 1 - \frac{\sum_{h=1}^L N_h \sigma_h^2}{N \sigma^2} = 1 - \frac{SSW}{SST} \quad (12)$$

$$SSW = \sum_{h=1}^L N_h \sigma_h^2 \quad (13)$$

$$SST = N \sigma^2 \quad (14)$$

The q ranges from 0 to 1, which represents the extent variable X manifest to dependent variable Y spatial heterogeneity. A larger value of q indicates a more pronounced spatial

heterogeneity of Y. If the value of q is larger, it means that the driving factor X has a stronger explanatory power on the dependent variable Y, and vice versa.

L represents the number of classification categories (zone) of variable X or Y. N_h and N are the number of units of layer h and the entire study area, respectively. σ_h^2 and σ^2 are the variance of layer h and Y of the entire study area, respectively. SSW is the sum of within-stratum variance, and SST is the total variance of the whole region.

(2) Interaction detector

The Interaction detector evaluates whether the interaction of driving factors X1 and X2 will increase or decrease the explanatory power of the dependent variable y, or whether the effects of these factors on Y are independent of each other.

Firstly, calculate the q values of Y for two factors X1 and X2: q (X1) and q (X2), respectively. Then, calculate the q value when they interact: q (X1∩X2). Finally, q (X1), q (X2) and q (X1∩X2) are compared. It can be categorized into types as seen in Table 4.

Table 4. Classifications of interaction of independent variable X.

Classifications of Interaction	Judgement
Single factor non-linear attenuation	$\text{Min} [q (X1), q (X2)] < q (X1 \cap X2) < \text{Max} [q (X1), q (X2)]$
Non-linear attenuation	$q (X1 \cap X2) < \text{Min} [q (X1), q (X2)]$
Non-linear enhancement	$q (X1 \cap X2) > q (X1) + q (X2)$
Double factor enhancement	$q (X1 \cap X2) > \text{Max} [q (X1), q (X2)]$
Independent	$q (X1 \cap X2) = q (X1) + q (X2)$

3. Results and Analysis

3.1. Land Use Changes in the Chaobai River Region

Based on the annual land use data of the Chaobai River region in 2001, 2005, 2009, 2013 and 2017, the land use dynamics of each land use class during the study period was calculated by Equation (1). A significant increase in the dynamics of land use for grassland, urban land, industrial and mining land and water was observed between 2001 and 2005, as shown in Table 5 below. Grassland had the quickest growth rate, with an average annual growth rate of 17.28%, followed by urban land. The land use dynamics of forest and rural settlements showed a significant decrease. The dynamics of agricultural land demonstrated a notable decline from 2005 to 2009, while the dynamics of construction land continued to climb. This was the only period when the dynamics of water in the research region exhibited a decline. In 2009–2013, only grassland and cropland showed a substantial decline in land use dynamics, while all other land use classes showed a rise, particularly in the areas used for industrial and mining land, forest and water. The dynamics of grassland and water increased between 2013 and 2017. During this time, the dynamics of forest and cropland displayed a consistent change.

Table 5. Land use dynamics of the Chaobai River region in 2001–2017.

Year	Agricultural Land (%)				Construction Land (%)		
	Cropland	Forest	Grassland	Waters	Urban Land	Rural Settlements	Industrial and Mining Land
2001–2005	−0.22	−6.82	17.28	11.31	15.93	−10.87	9.49
2005–2009	−0.72	−2.18	−0.83	−7.36	1.56	10.49	1.58
2009–2013	−2.08	10.18	−14.11	11.5	3.91	1.2	11.66
2013–2017	−0.06	−0.59	6.15	2.75	1.84	−3.58	−3.04

Overall, the different land use classes in the research area saw a substantial change between 2001 and 2017. The dynamics of waters in agricultural land showed a increasing trend, while forest, grassland and cropland exhibited a falling trend and the dynamics of land classes other than rural settlements in construction land increased.

As can be seen from Table 6, the area of cropland and rural settlements decreased significantly, while the amount of urban land and waters increased. Among them, the transfer out of cropland is larger and it is being transferred out mostly towards water, urban land and rural settlements. The overall area moved to urban land and rural settlements is 614.752 km², while the area transferred to water is 251.813 km². The main transfer out of rural settlements is in the direction of cropland and urban land.

Table 6. Land use transfer matrix of the Chaobai River region in 2001–2017 (km²).

Year	Land Use Class	2017							Sum
		Cropland	Forest	Grassland	Urban Land	Rural Settlements	Industrial and Mining Land	Waters	
2001	Cropland	2286.870	1.805	3.955	361.059	253.693	3.457	251.813	3162.652
	Forest	3.859	40.747	0.532	0.608	0.700	6.169	0.401	53.015
	Grassland	1.789	3.569	3.483	0	0.492	0.002		9.335
	Urban Land	75.833	0	0	249.967	16.775	0.021	3.546	346.142
	Rural Settlements	340.726	1.499	0.121	118.184	218.478	1.563	17.493	698.063
	Industrial and Mining Land	1.235	0.734	0	0	0.065	9.084	0	11.117
	Waters	75.196		0.194	17.803	12.747	0.716	145.658	252.314
Sum	2785.508	48.353	8.285	747.620	502.950	21.011	418.911	4532.638	

An analysis of the inner mechanisms of the change shows that the urbanization of the study area has been further strengthened under the trend of cooperative development in Beijing–Tianjin–Hebei, while the local government is paying more attention to the role of the Chaobai River as an ecological barrier and major water source for the capital. Additionally, agricultural land is increasingly being encroached upon by construction land, while some cropland is being turned into waters to enhance the ecosystem services offered by the Chaobai River region.

In general, the land use pattern in the study region underwent significant changes between 2001 and 2017, including area changes, spatial changes and quality changes, etc. This study focuses on introducing the area changes and spatial changes of land use classes in the study area. As shown in Table 6, other land classes in agricultural land are increasingly disappearing, while the area of water is gradually growing. The area of construction land has dramatically grown, with urban land growing at the quickest rate.

This changing feature is compatible with the development strategy of the Chaobai River region to be water-based and protect water sources. As the most important primary source of water in Beijing, the protection of water sources is a prerequisite for the development and construction of the Chaobai River region. In addition, it is the epitome of Beijing–Tianjin–Hebei’s synergistic development and the substantial increase in construction land is consistent with its current situation of grasping major opportunities of the accelerating urbanization process.

Additionally, a comparison of the land use maps of the Chaobai River region from 2001 and 2017 (see Figure 2) reveals that, in terms of spatial layout, the construction land in the region is becoming more concentrated and gradually distributed in a cluster in the northwest and central regions. In 2001, the cropland was evenly spread, but by 2017, it had also started to become increasingly dispersed. The waters were sparsely distributed throughout the whole research region in 2001, but in 2017 their area had significantly enlarged and they showed a banded and faceted distribution towards the southeast.

As a microcosm of the development of Beijing–Tianjin–Hebei, the Chaobai River region has witnessed a continual reorganization and integration of the land use structure of the region, with the conflict between people and land being continuously relieved and the structure continuously rationalized.

3.2. Carbon Emission from Land Use

The land use carbon emission of the Chaobai River region from 2001 to 2017 is computed using data on energy consumption, land use, remote sensing images, and carbon (see Table 7).

Table 7. Main land use carbon emission of the Chaobai River region from 2001 to 2017.

Year	Land Use Class	Beijing (t)	Total Emissions of Beijing (10 ⁴ t)	Tianjin (t)	Total Emissions of Tianjin (10 ⁴ t)	Hebei (t)	Total Emissions of Hebei (10 ⁴ t)	Total Emissions of Basin (10 ⁴ t)
2001	Cropland	60,885.70	228.95	50,818.59	120.28	41,617.27	263.34	612.58
	Forest	−1995.84		−7.3416		−1103.55		
	Grassland	−7.04		−0.0156		−25.222		
	Waters	−464.90		−1096.82		−116.257		
	Construction Land	2.2 × 10 ⁶		1.1 × 10 ⁶		2.5 × 10 ⁶		
Others	−0.04	0	−0.82115					
2005	Cropland	56,708.87	285.05	49,240.13	78.40	40,524.95	386.73	750.18
	Forest	−1938.76		−6.53016		−974.404		
	Grassland	−7.61		−0.064		−20.9018		
	Waters	662.43		−1735.83		−149.886		
	Construction Land	2.7 × 10 ⁶		0.7 × 10 ⁶		3.8 × 10 ⁶		
Others	−0.04	0	−1.62785					
2009	Cropland	52,865.59	367.68	48,344.2	154.72	39,167.34	323.23	845.63
	Forest	−1997.48		−6.4722		−954.015		
	Grassland	−8.70		−0.3348		−19.5336		
	Waters	−467.56		−1877.64		−184.581		
	Construction Land	3.6 × 10 ⁶		1.5 × 10 ⁶		3.2 × 10 ⁶		
Others	−0.06	0	−2.2741					
2013	Cropland	52,865.59	388.42	48,344.2	208.99	39,167.34	744.30	1341.71
	Forest	−1997.48		−6.4722		−954.015		
	Grassland	−8.70		−0.3348		−19.5336		
	Waters	−467.56		−1877.64		−184.581		
	Construction Land	3.8 × 10 ⁶		2 × 10 ⁶		7.4 × 10 ⁶		
Others	−0.06	0	−2.2741					
2017	Cropland	48,805.73	388.16	47,189.77	198.14	36,544.78	488.64	1074.94
	Forest	−2099.70		−55.4742		−985.288		
	Grassland	−4.09		−0.16		−19.488		
	Waters	−525.89		−1868.62		−205.183		
	Construction Land	3.8 × 10 ⁶		1.9 × 10 ⁶		4.9 × 10 ⁶		
Others	−0.08	0	−1.6837					

Between 2001 and 2017, carbon emissions from cropland in the study region decreased year on year. Forest and water also played corresponding roles as carbon sinks, but the total carbon emissions in the region still increased steadily year after year, which was attributed to the constant rise in energy consumption brought on by the continuous development strategy of the Beijing–Tianjin–Hebei synergy and the active socio-economic activities. In order to achieve the goal of synergistic development in the Beijing–Tianjin–Hebei region, it is necessary to concentrate on the construction land as the main carbon source, analyze the demand for various types of energy in different regions in depth and actively develop low-carbon technologies.

Based on the carbon emission data of the Chaobai River region, the carbon emission statistics of each river section are presented (see Figure 3). The trend of carbon emissions from land use in the Chaobai River region may be separated into three periods, as shown by the graph.

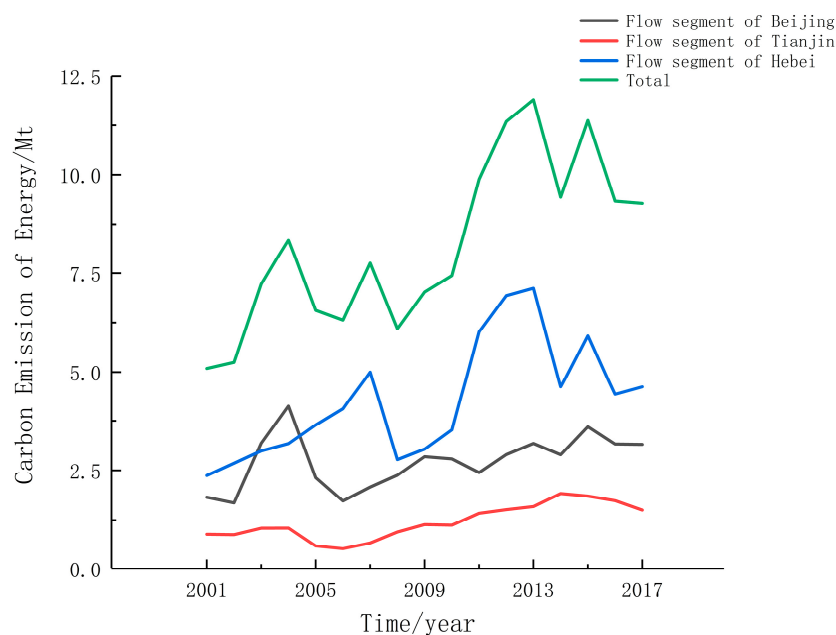


Figure 3. The carbon emissions from construction land of the Chaobai River region.

The first phase was from 2001 to 2009. During this period, there were successive peaks of carbon emissions from construction land in the Beijing and Hebei streams of the Chaobai River. In the context of continued urbanization and preparations for the 2008 Beijing Olympics, the study area saw a massive expansion of construction land and an increasing demand for fossil fuels.

The second phase was between 2009 and 2015. When the Asian financial crisis started in 2009, China invested heavily in infrastructure construction to eliminate the economic impact, which led to new highs in carbon emissions during this period. In 2010, China published the National Plan of Main Functions and started to acknowledge the significance of environmental preservation and make changes and strategies.

The third phase was from 2015 to 2017. During this time, China proposed the supply side structural reform and promulgated the “Beijing–Tianjin–Hebei Synergistic Development Plan Outline” in 2015, which indicated that the current development priorities are to decongest Beijing’s non-capital functions and promote the synergistic development of Beijing, Tianjin and Hebei provinces and cities. Under the policy, some heavy industrial enterprises in Beijing were relocated to Tianjin and the province of Hebei. From Figure 3, it can be seen that the total regional carbon emission from construction land continued to decline during this period, and the carbon emissions from construction land in the three provinces and cities have relatively similar trends, which also reflects that socio-economic activities have a certain regular influence on regional land use carbon emissions.

3.3. LMDI and Outcome Analysis

According to the LMDI driver decomposition method [52], the land use carbon emissions in the study area were decomposed and the relationship between the four influencing factors of carbon emission intensity, economic development level, land use efficiency and construction land scale and the changes in land use carbon emissions were explored in depth, and the results obtained are shown in Tables 8 and 9.

Table 8. The carbon emission factor decomposition in the Chaobai River region (10^4 t).

Year	Carbon Emission per Unit of GDP C_{Ai}	GDP per Capita ΔC_{Bi}	the Number of People per Unit of Land Area ΔC_D	the Construction Land Area ΔC_S
2001–2005	−2.12	3.31	−0.80	0.98
2005–2009	−5.45	6.07	−0.60	0.94
2009–2013	−1.71	6.03	−0.91	1.55
2013–2017	−6.81	3.02	0.16	0.96
Total	−16.08	18.43	−2.15	4.43

Table 9. The contribution rate of carbon emission factor decomposition (%).

Year	Carbon Emission per Unit of GDP C_{Ai}	GDP per Capita ΔC_{Bi}	the Number of People per Unit of Land Area ΔC_D	the Construction Land Area ΔC_S
2001–2005	−153.89	240.69	−58.10	71.29
2005–2009	−571.26	635.60	−63.28	98.94
2009–2013	−34.41	121.54	−18.37	31.23
2013–2017	255.12	−113.11	6.02	−35.99
Total	−504.44	884.73	−145.76	165.47

As can be shown from Table 8, the economic development level factor has a positive driving effect on the growth of carbon emissions in the Chaobai River region. From 2001 to 2005, the level of economic development contributed up to nearly 30,000 tons. The contributions from 2005 to 2009 and 2009 to 2013 both exceed 60,000 tons, with the largest contribution from 2005 to 2009 and the least contribution from 2013 to 2017. Between 2001 and 2017, the gross domestic product (GDP) of the Chaobai River region increased from RMB 41.5 billion to RMB 406.6 billion, with an average annual growth rate of 35%. As a result of this rapid economic expansion, the region's total carbon emissions rose by 4.6 million tons.

The contribution of the construction land scale factor to the growth of carbon emissions from land use in the study area is second only to the influence of economic development. With the development of regional economy, the scale of construction land has increased dramatically and the socio-economic activities that take place there require a significant amount of fossil fuel, which directly contributes to the sharp rise in carbon emissions.

Carbon emission intensity, which is the main negative driver of carbon emissions affecting land use in the study area, has been in a decreasing trend since 2001, indicating that the adjustment of energy consumption structure in the study area has achieved certain emission reduction results. In the future, the Chaobai River region still needs to further optimize the energy use structure, so as to effectively reduce carbon emission intensity. Although land use efficiency has one of the least substantial effects on carbon emissions, it also plays a certain inhibitory role.

The cumulative contribution rate of the factors can be further calculated as below.

In terms of the cumulative contribution of the factors influencing carbon emissions, among the positive drivers, the cumulative contribution of the level of economic development and the scale of construction land from 2001 to 2017 are 884.73% and 165.47%, respectively. Among the negative drivers, the cumulative contribution rates of emissions per unit of GDP and land use efficiency were 504.44% and 145.76%, respectively. The level of economic development became the most important driver of land use carbon emission growth within the study area.

3.4. Driving Factors Analysis of Land Use Change

Based on the LMDI model presented above, land use scale is a significant factor in the growth of land carbon emissions in the Chaobai River region, so it is necessary to further explore the intrinsic drivers of land use change and develop corresponding policy measures accordingly. This study selects indicators based on the characteristics of the

Chaobai River region as the driving factors of land use change through three dimensions: physical geography, social living conditions and economic development level. The driving factor is the independent variable X , which is a type quantity, and the dependent variable Y value indicates the type of land use change in the study area, which is a numerical quantity. The independent variable X includes seven indicators, which are precipitation, slope, elevation, temperature, population density, GDP and night light brightness.

The explanation of each factor is shown in Table 10 below.

Table 10. Driving factors of land use change.

Dimensions	Indicators	Explanation
Physical Geography	X1: Elevation (m)	Elevation of the Chaobai River
	X2: Slope (°)	Slope of the Chaobai River
	X3: Precipitation (mm)	Precipitation of the Chaobai River
	X4: Temperature (°C)	Temperature of the Chaobai River
Social Living Conditions	X5: Population density (person/km ²)	Population density of the Chaobai River
Economic Development Level	X6: GDP (RMB million/km ²)	GDP of the Chaobai River
	X7: Night light brightness	Night light brightness of the Chaobai River

3.4.1. The Result of Driving Factors Detection

Combining regional conditions, each driver was reclassified by using ArcMap 10.3 software. The Chaobai River area was partitioned into regular grids, and each grid center was sampled. The land use change class and each driver for each year were extracted to the sampling points in the cell grid. Then, factor detector was used to calculate the degree of influence of each driver on land use change in Chaobai River. The result is shown in Figure 4 below. Since elevation and slope did not pass the hypothesis test at the 5% level in some years, and their explanatory power was low, these two factors were excluded. The results of factor detection and interaction are only presented for five factors: X3 (Precipitation), X4 (Temperature), X5 (Population density), X6 (GDP) and X7 (Night light brightness).

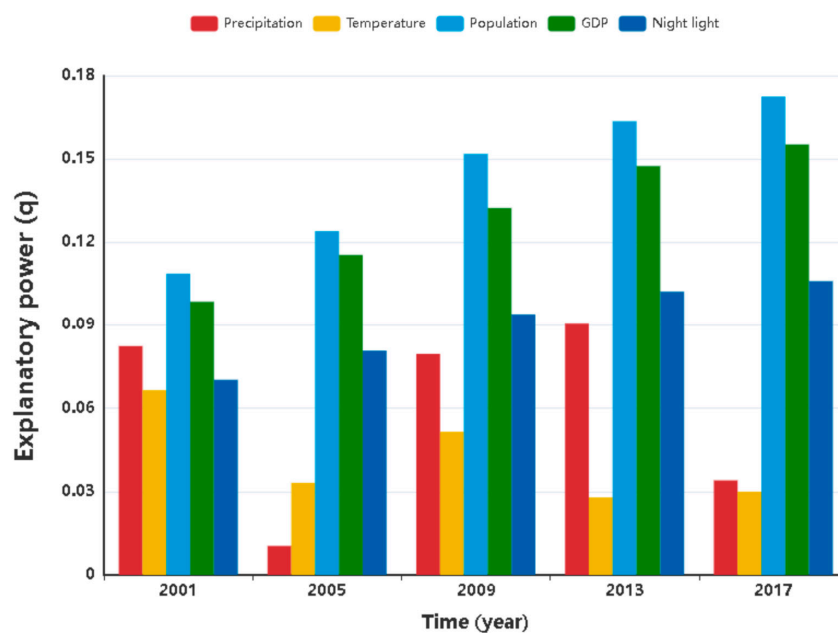


Figure 4. The detection result of land use change driving factors.

The results of factor detection reflect the explanatory power of each factor on land use change in the Chaobai River region. According to the results of factor detection for each year, in 2001, the explanatory power of each factor on land use change in the Chaobai

River region was ranked from largest to smallest as follows: population density > GDP > precipitation > night light brightness > temperature. The strongest explanatory power ($q > 0.1$) is X5 (population density), followed by X3 (precipitation) and X6 (GDP), both of which had q values < 0.1. Population density measures how concentrated a region's population is and it has a significant impact on land use change. This result indicates that the land use change in the Chaobai River region in 2001 was mainly influenced by population.

In 2005, the explanatory power of each factor on land use change in the Chaobai River in descending order was as follows: population density > GDP > night light brightness > temperature > precipitation. The factors with strong explanatory power are X5 (population density) and X6 (GDP), whose q -values are greater than 0.1. GDP, and population density can reflect the level of regional economic development. Compared with 2001, the explanatory power of GDP on land use change has been strengthened, and it can be seen that population and economic development have become the dominant factors influencing regional land use change in this period, which is closely related to the accelerated urbanization and rapid development of economic construction in the Beijing–Tianjin–Hebei region in this period.

In 2009, the explanatory power of each factor on land use change in the Chaobai River in descending order was as follows: population density > GDP > night light brightness > precipitation > temperature. The explanatory power of the three factors, X5 (population density), X6 (GDP) and X7 (night light brightness), increased continuously during this period. It indicates that socio-economic conditions during this period became an absolute factor in determining changes in land use patterns in the Chaobai River region.

In 2013, the explanatory power of each factor for land use change in the Chaobai River is the same as in 2009. The explanatory power of the three factors, X5 (population density), X6 (GDP) and X7 (night light brightness), further increased in this period, with their q -values all reaching above 0.1. During this period, the explanatory power of precipitation as a climatic factor reaches the maximum and the influence of climatic factors on land use change is more prominent. Meanwhile, the Chaobai River serves as an ecological barrier in the Beijing–Tianjin–Hebei region, reflecting that the construction of ecological civilization in the Chaobai River has achieved some success.

In 2017, the explanatory power of each factor on land use change in the Chaobai River in descending order was as follows: population density > GDP > night light brightness > precipitation > temperature. The explanatory power of three factors, X5 (population density), X6 (GDP) and X7 (night light brightness), was still increasing in this period, but its magnitude was gradually stabilizing. The explanatory power and influence of precipitation are drastically reduced when compared to 2009 and 2013, which may be strongly related to the decline in cropland area in the Chaobai River region during this period.

Throughout the study period, the influence of the driving factors on land use change in the Chaobai River region varied from period to period, but factors such as population, GDP, and night light brightness all had strong explanatory power. The socioeconomic factors were always stronger than the natural climatic factors, with population always been the most influential factor leading to regional land use change. The Chaobai River region has a superior geographic location since it is situated in the crucial area for the coordinated growth of the Beijing–Tianjin–Hebei urban agglomeration. With rapid economic development and accelerating urbanization, economic conditions directly determine the land use change pattern of this region to a large extent.

3.4.2. The Result of Interaction Detection

The cross-detection reflects the difference in the effect of the joint action of different drivers on land use change compared with the single-factor action [53]. The results of cross-detection for each year are shown in Figure 5. As can be seen from Figure 5 below, the results of interaction detection between different driving factors for each year from 2001 to 2017 mainly show a two-factor enhancement or non-linear enhancement effect,

and there is no mutual independence or weakening, i.e., the explanatory power of the interaction between factors on land use change is enhanced to varying degrees relative to the single-factor effect [54]. It shows that the influence of the interaction among the drivers is huge and their interaction plays a decisive role in land use change in the Chaobai River region. In addition, it also confirms that land use change is a complex process of interaction between different drivers [55].

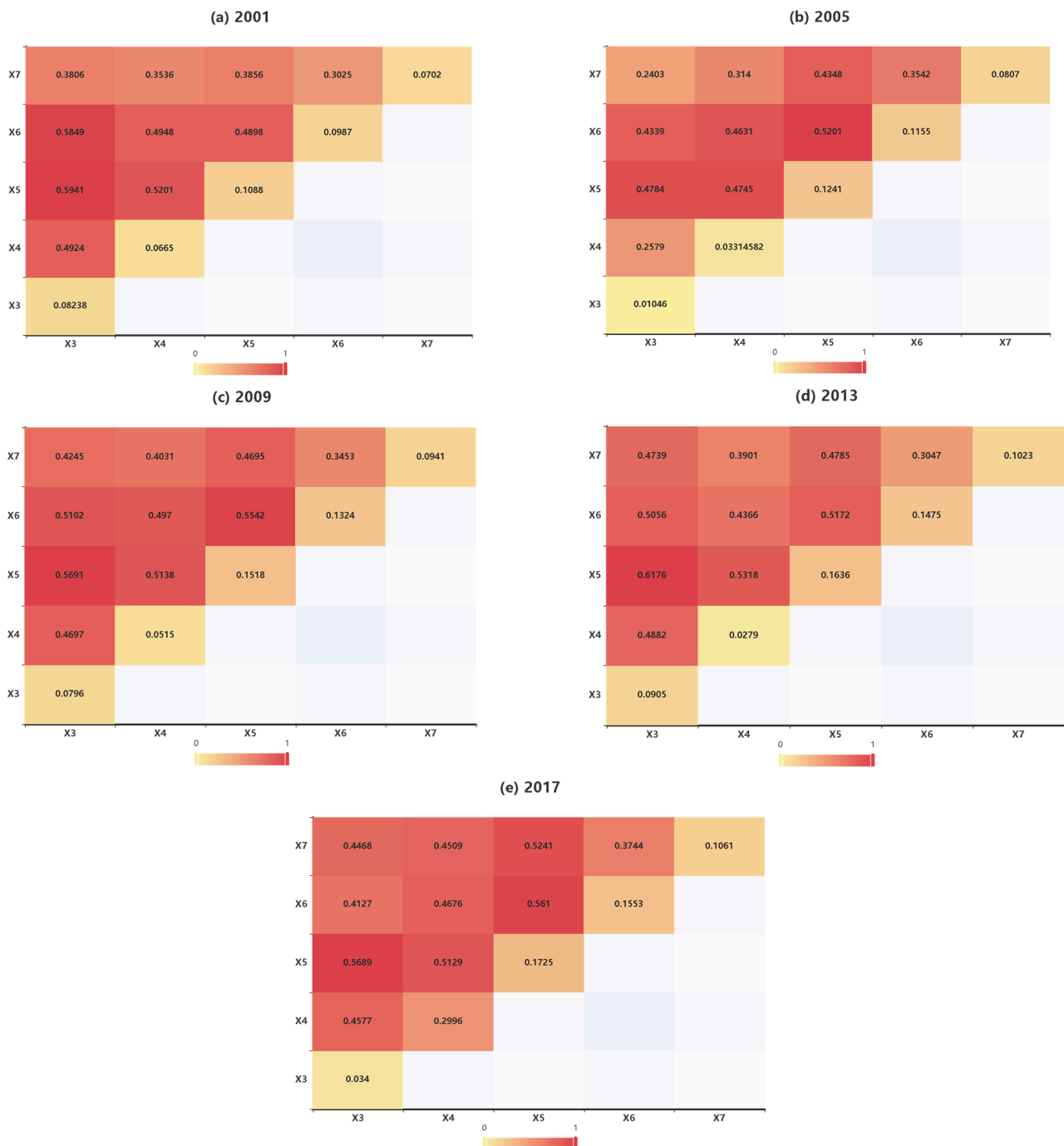


Figure 5. Results of interaction detection.

In 2001, the explanatory powers of the interaction of precipitation with temperature, population density, and GDP were 0.4924, 0.5941 and 0.5849, respectively. The explanatory powers of the interaction of temperature with population density and GDP were 0.5201 and

0.4948, respectively, and the explanatory power of the interaction of population density and GDP was 0.4898, indicating that precipitation, population density, GDP and other factors jointly drove the land use change.

In 2005, the explanatory powers of the interaction of population density with precipitation and temperature were 0.4784 and 0.4745, respectively. The explanatory powers of the interaction of GDP with precipitation, temperature and population density were 0.4339, 0.46631 and 0.5201, respectively, and the explanatory power of the interaction of population density with night light brightness was 0.4348. It reflects that, with the passage of time, GDP, population density, night light brightness, precipitation and temperature are the main factors governing land use change.

In 2009, the explanatory powers of the interaction of precipitation with temperature, population density, GDP and night light brightness were 0.4697, 0.5691, 0.5102, and 0.4245, respectively. The explanatory powers of the interaction of temperature with population density, GDP and night light brightness were 0.5138, 0.497 and 0.4031, respectively, and the explanatory power of the interaction of population density with GDP and night light brightness were 0.5542 and 0.4695, among which the interaction between precipitation and population density has the strongest explanation for the regional land use change, indicating that the land use change in this period is influenced by multiple factors.

In 2013, the explanatory power of the interaction between precipitation and population density was 0.5689. The explanatory power of the interaction between temperature and population density was 0.5129, and the explanatory power of the interaction of population density with GDP and night light brightness were 0.561 and 0.5241, indicating that population density, precipitation, GDP and night light brightness continued to jointly dominate the land use change in that period.

In 2017, the interaction of both precipitation and population density still had the strongest explanatory power, with a q-value of 0.6176. The explanatory power of the interaction of temperature and population density was 0.5318, and the explanatory power of the interaction between population density and GDP was 0.5172. It indicates that population density, precipitation, and GDP became the key factors dominating regional land use changes in that period.

From the whole study period, the mechanisms of interaction of land use change factors differed significantly between periods. The degree of interaction between climate factors such as precipitation and temperature and other factors was stronger in the early part of the study period (2001–2005). However, during the middle and later portions of the study period (2009–2017), population density and socio-economic level became the key factors that jointly drive land use change. In addition, strong explanatory power exists in the interactions of population density and GDP with other driving factors at all times, indicating that these factors are more active on land use change in all periods and these factors together advance regional land use change.

4. Discussion

In 2015, the Chinese government considered and adopted the Outline of the Beijing–Tianjin–Hebei Cooperative Development Plan, which aims to decongest Beijing’s non-capital functions, create a future-oriented capital economic circle, promote innovation in regional development institutions and mechanisms, investigate new models of regional economic development, and meet the needs for coordinated and sustainable development of population, economy, resources, and environment [56–58]. In this context, urbanization and industrialization in the Beijing–Tianjin–Hebei region have further continued to advance rapidly, industries have undergone substantial industry transfers, and regional land use structures have undergone continuous reorganization [59]. The Chaobai River flows through Tongzhou and Shunyi districts in Beijing, Baodi district in Tianjin, and Sanhe, Xianghe and Dazhan Hui autonomous counties in Hebei province, which are the “golden areas” bordering Beijing–Tianjin–Hebei. Its land use structure change characteristics are increasingly becoming a microcosm of land use change in the Beijing–Tianjin–Hebei region.

Based on the structural land use change characteristics of the region, this study systematically analyzes the land use change characteristics of the Chaobai River region by using two aspects: land use dynamic attitude and land use transfer matrix. Compared with international studies that concentrate on the spatial and temporal patterns of land use carbon emission effects in large regions such as cities, this research focuses on the analysis of small water bodies and innovatively selects the Beijing–Tianjin–Hebei flow section of the Chaobai River, focusing on the ecological role of river water bodies in urban development and the role of Beijing–Tianjin–Hebei as a national key urban cluster. The period 2001–2017 was chosen as the study period because China has begun a rapid urbanization process since its accession to the World Trade Organization (WTO) in 2001, and the conflict between people and land has become more apparent while society has undergone drastic changes.

Therefore, it is socially important to research the changes in land use patterns and carbon emissions during this period. In this study, data extracted from authoritative statistical yearbooks were used to estimate and calculate regional carbon emissions based on the IPCC inventory method using carbon emission factors and carbon emission models for energy consumption, and it was determined that carbon emissions in this study area showed a general upward trend from 2001 to 2017. The main carbon source is construction land, which carries the main socio-economic activities, and the main carbon sinks are forest and waters. In addition, it is worth mentioning that, since the scale of the study is at the county and district level, accurate energy consumption data are difficult to obtain. Therefore, based on the results of existing studies, this study estimated the carbon emissions of construction sites in counties lacking energy data using energy consumption data per unit of GDP.

In addition, the results of this study are generally highly reliable and generally consistent with previous studies. For example, some previous studies suggested that GDP per capita growth was a major factor driving carbon emissions in China [39,60], and this research decomposes and analyzes the influencing factors of carbon emissions by using the well-established LMDI model, and also suggested that the degree of economic development is revealed to be the most significant driver of carbon emissions increase in the study region. It suggests that the Chaobai River, which is an important part of the Beijing–Tianjin–Hebei urban agglomeration of China's three largest urban agglomerations, is generally in line with the country's overall rate of economic development, and that the factors driving its increase in carbon emissions are similar to those of China as a whole. Additionally, this study also uses the geographical detector to discover that the population and GDP are the most significant factors influencing land use change in the study area, i.e., the level of regional economic development plays a dominant role in land use pattern change. Meanwhile, the inter-factor interactions showed a bivariate or nonlinear enhancement in all years, indicating that the inter-factor interactions were enhanced relative to the single factor, further contributing to land use change.

Taken together, the changes in land use patterns and carbon emissions in the research area coincide with the economic and social development trends of the region. Compared with previous studies, this study chooses more comprehensive factors and further considers night light brightness, which reflects socioeconomic conditions, as a driving factor, contributing to a systematic understanding of the processes that are responsible for land use change. At the same time, the geographical detector has unique advantages in explaining the spatial heterogeneity of geographic phenomena that other methods do not have. This research analyzes the mechanism of land use change from the perspective of factor interaction in addition to demonstrating the strength of each element's influence on land use change from a single factor aspect. It makes up for the shortcomings of the traditional approaches that are unable to explain the influence mechanism of interaction. Finally, this study discusses and explores the methods of optimizing the land use structure to achieve the low-carbon collaborative development in the study region, with a view to providing reference for the in-depth promotion of the Beijing–Tianjin–Hebei collaborative development strategy and the optimization and improvement of related policies.

This research has several drawbacks. The land use data is generated through the interpretation of remote sensing image data, and it is difficult to obtain accurate county-level data, which may affect the accuracy of the calculation results. In addition, the current technical standards for carbon emission accounting have been largely developed as well, and the carbon emission coefficients used in this study primarily refer to the findings of other experts and scholars; due to the differences in the study areas, there are certain errors in measuring the land use carbon emissions in the Chaobai River area with this method. There are some limitations in the usage of the geographical detector. The explanatory power of each driver to land use change is represented by absolute values, so that the direction of influence of each driver to land use change cannot be accurately judged. In addition, the discrete nature of the independent variables, the density of the grid and the number of sampling points and other treatments can affect the explanatory power changes of the driving factors, and these issues still need to be further explored. Further integration of the geographical detector with traditional methods will be considered in the future to give full play to the advantages of each method.

5. Conclusions

Based on land use data and fossil energy consumption statistics, this study analyzed the spatial and temporal characteristics of land use pattern changes in the region and calculated the net carbon emissions from various land uses. It also used the LMDI model to determine the cumulative impact of each influencing factor on changes in carbon emission, further analyzed the cumulative contribution of each influencing factor to carbon emissions in the study area, and deciphered the inner mechanism of carbon emissions. In addition, it explored the inner mechanism of the land use change in the region by using the geographical detector. The spatiotemporal changes in carbon emissions and land use reflect the development characteristics of the Chaobai River Basin under the guidance of the Beijing–Tianjin–Hebei collaborative development strategy.

The main research results are as follows:

(1) During the study period, the land use pattern of the study area is mainly agricultural land and construction land, with cropland decreasing and urban land increasing year by year, while the main transfer direction of cropland is to construction land and water. The spatial and temporal changes of land use patterns in the study area are consistent with the “water-based” development concept and the rapid urbanization process in the area.

(2) Carbon emissions from land use have shown a generally increasing trend, largely overlapping with the socio-economic development process in the region. The energy consumption caused by human socio-economic activities carried by construction land became the largest source of carbon emissions, accounting for up to 90%. In contrast, forest and water, as carbon sinks, have played a role in reducing the rise in carbon emissions.

(3) The level of economic development and the scale of construction land play a major positive driving role in the growth of carbon emissions, so the study area should pay attention to the innovation of the economic development model, and continue to take the low-carbon sustainable development path. The carbon emission intensity and land use efficiency play a suppressive role, so the project should pay attention to improving energy use efficiency, reducing the unit GDP energy consumption, and promoting the intensive and economical use of the region.

(4) The results of geographical detector show that the strength of each driver varies under different periods, but population and GDP are always important drivers with the strongest explanatory power for land use pattern changes. The inter-factor interactions showed a bivariate or nonlinear enhancement in all years.

6. Recommendations

Under the goals of carbon peaking and carbon neutrality, understanding how to control the growth of carbon emissions while ensuring high-quality economic and social development has become a top priority for the development of Beijing–Tianjin–Hebei. The

scientific synergy of carbon emissions at the spatial scale of Beijing–Tianjin–Hebei has also become an important part of the collaborative development. Based on the positioning of the three provinces and cities in the Beijing–Tianjin–Hebei cooperative development strategy, this study aimed to explore the optimization of land use structure and provide reference for the further promotion and optimization of low-carbon cooperative development in the Beijing–Tianjin–Hebei region, mainly as follows:

(1) Accelerate industrial transformation and establish low-carbon sectors. The Chinese government should continuously advance structural reform on the supply side, fully exploit the comparative advantages of various regions, continuously improve the balance and coordination of development, carry out scientific transfer of primary and secondary industries based on urban positioning, concentrate on accelerating the docking and collaboration of industries and form a reasonable distribution of industries between regions. At the same time, it should formulate relevant policies to attract low-carbon enterprises to land, promote the construction of the Beijing Tongzhou sub-center and ESG Green Industry Innovation Center.

(2) Control the proportion of construction land. The construction land is the largest source of carbon in the Beijing–Tianjin–Hebei region, while its land use scale has a positive effect on the growth of carbon emissions. Therefore, to encourage low carbon development in the Beijing–Tianjin–Hebei region, the layout of land use structure should be scientifically planned according to the carbon source/sink intensity of various land use methods, limiting the expansion of construction land, considering ecological requirements, appropriately increasing the area of land classes with strong carbon sink capacity (e.g., forest and grassland) and expanding the area of urban greenery while ensuring the red line of cropland [61], and reasonably laying out production, living and ecological spaces.

(3) Promote the development of low-carbon technologies and adjust the energy structure. Considering that energy consumption is the main production activity of construction land as a carbon source, efforts should be made to accelerate the modification of the energy structure and system. At this stage, the development of the Beijing–Tianjin–Hebei region still heavily relies on conventional energy sources such as coal and oil. As a result, it is important to fully utilize the advantages of Hebei Province's abundant natural resources, including wind and solar energy, as well as the advantages of the confluence of scientific research institutions in Beijing and Tianjin to jointly promote clean energy development and low-carbon technology innovation, improve the regional energy market synergy mechanism, and build a trading platform for renewable resources in Beijing–Tianjin–Hebei region.

(4) Give full play to the role of the government and raise the awareness of citizens. In order to achieve low-carbon synergistic development in the Beijing–Tianjin–Hebei region, the government must fully utilize its management and supervision functions, strengthen top-level design, concentrate on the carbon market's function, explore effective power mechanisms to reduce pollution and reduce carbon synergies, and realize the incentive mechanism for businesses to reduce carbon emissions through carbon emissions trading.

Author Contributions: Conceptualization, C.L. and R.X.; Methodology, C.L., K.X. and R.X.; Guidance, Y.C.; Formal Analysis, C.L., K.X. and R.X.; Investigation, Y.L.; Project administration, K.X.; Validation, C.L.; Visualization, C.L.; Writing—original draft, C.L., K.X., R.X. and Y.L. All authors have read and agreed to the published version of the manuscript.

Funding: This research was financially supported by China University of Geosciences (Beijing) Student Innovation and Entrepreneurship Training Program (S202211415159).

Acknowledgments: Thank you to everyone who contributed to this study.

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

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