

Article

Spatiotemporal Evolution and Driving Factors of the Relationship Between Land Use Carbon Emissions and Ecosystem Service Value in Beijing-Tianjin-Hebei

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Abstract

Land use change significantly affects regional carbon emissions and ecosystem service value (ESV). Under China's Dual Carbon Goals, this study takes Beijing-Tianjin-Hebei, experiencing rapid land use change, as the study area and counties as the study unit. This study employs a combination of methods, including carbon emission coefficients, equivalent-factor methods, bivariate spatial autocorrelation, and a multinomial logit model. These were used to explore the spatial relationship between land use carbon emissions and ESV, and to identify their key driving factors. These insights are essential for promoting sustainable regional development. Results indicate the following: (1) Total land use carbon emissions increased from 2000 to 2015, then declined until 2020; emissions were high in municipal centers; carbon sinks were in northwestern ecological zones. Construction land was the primary contributor. (2) ESV declined from 2000 to 2010 but increased from 2010 to 2020, driven by forest land and water bodies. High-ESV clusters appeared in northwestern and eastern coastal zones. (3) A significant negative spatial correlation was found between carbon emissions and ESV, with dominant Low-High clustering in the north and Low-Low clustering in central and southern regions. Over time, clustering dispersed, suggesting improved spatial balance. (4) Population density and cultivated land reclamation rate were core drivers of carbon-ESV clustering patterns, while average precipitation, average temperature, NDVI, and per capita GDP showed varied effects. To promote low-carbon and ecological development, this study puts forward several policy recommendations. These include implementing differentiated land use governance and enhancing regional compensation mechanisms. In addition, optimizing demographic and industrial structures is essential to reduce emissions and improve ESV across the study area.

Keywords: land use carbon emissions; ecosystem service value; spatiotemporal evolution; driving factors; county scale; the Beijing-Tianjin-Hebei region



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1. Introduction

Land use carbon emissions refer to the greenhouse gases released due to changes in land use patterns, such as the conversion of cropland into construction land, as well as from ongoing land use activities, including agricultural cultivation and urban

development [1,2]. Such emissions have become the second-largest source of global greenhouse gases after fossil fuel combustion, significantly contributing to climate change [3]. ESV refers to the monetary or non-monetary valuation of the benefits that ecosystems provide to human society [4,5]. These benefits encompass four broad categories: provisioning services, such as the supply of food, water, and raw materials; regulating services, such as carbon sequestration, climate and water regulation, and soil retention; cultural services, including recreation and aesthetic enjoyment; and supporting services, such as nutrient cycling and biodiversity maintenance [6]. ESV is typically quantified by converting the biophysical outputs of these services into economic terms through approaches such as market pricing, replacement cost, or benefit transfer methods. It serves as a crucial indicator for quantifying the contribution of natural capital to human well-being, and is extensively utilized in the fields of ecological conservation, environmental economic accounting, and sustainable development decision-making [7].

The United Nations Sustainable Development Goals (SDGs) [8] and the Paris Agreement [9] have jointly established a global framework for climate governance. Within this framework, responding to climate change has become an urgent and shared responsibility for all humankind. The intensification of global warming and the increasing frequency of extreme weather events are exacerbating climate risks. At the same time, rising sea levels and the rapid loss of biodiversity pose severe threats to the foundations of human survival and development. The Paris Agreement sets the goal of limiting the global average temperature rise to well below 2 °C above pre-industrial levels, with an aspirational target of 1.5 °C. To achieve this, it calls for international cooperation on emission reduction, enhancement of ecosystem carbon sequestration, and the promotion of green and low-carbon transitions. China has actively responded to this global call and has deeply engaged in international climate governance. In 2020, China officially proposed the dual-carbon goals, namely carbon peaking and carbon neutrality, and subsequently introduced a series of policies to guide low-carbon development. A key policy document issued in 2021—*Working Guidance for Carbon Dioxide Peaking and Carbon Neutrality in Full and Faithful Implementation of the New Development Philosophy*—emphasizes the importance of enhancing ecosystem carbon sink capacity. It also highlights the close relationship between ESV and carbon emissions [10].

There exists a significant spatiotemporal interaction between land use carbon emissions and ESV [11–14]. This interaction arises from the joint influence of land use changes on both the carbon emission processes and ecosystem service functions. For example, the expansion of construction land typically leads to increased carbon emissions and undermines the regulatory and supportive functions of ecosystems. In contrast, ecological conservation and restoration efforts contribute to enhanced carbon-sequestration capacity and the improvement of multiple ecosystem services. The interaction between land use carbon emissions and ESV plays a critical role in shaping the global and regional climate governance frameworks. Against the backdrop of global climate change and China's "dual carbon" strategy, elucidating their spatiotemporal relationship and identifying the underlying driving factors have emerged as crucial research imperatives. Such understanding is essential for effectively implementing national climate policies and advancing sustainable development goals [7,15]. However, existing research remains limited in exploring the mechanisms behind these spatiotemporal associations. Many studies lack a systematic and integrated perspective, and the driving forces and interaction mechanisms behind the formation of spatial patterns are still poorly understood. To this end, this study incorporates land use carbon emissions and ESV into a dual-factor interaction framework. On this basis, a bivariate spatial autocorrelation model is used to examine the spatiotemporal dependence between the two factors. In addition, a multinomial logit regression model is

applied to identify the driving factors behind different interaction patterns. The research results can provide a scientific basis for formulating land use policies oriented towards ecological protection, and offer valuable references for achieving the coordinated goal of low-carbon development and sustainable ecosystem utilization.

The Beijing-Tianjin-Hebei region is a major driver of China's economic growth, marked by high energy consumption and substantial carbon emissions. Simultaneously, it functions as a national demonstration zone for ecological restoration and environmental improvement, making notable contributions to ecosystem service provision. Rapid urbanization and intensive land use changes have intensified human–environment conflicts and ecological pressures. These developments have resulted in irrational land use patterns, resource depletion, and worsening environmental quality. Counties, as the fundamental administrative units for urban–rural development and policy execution in China, play a critical role. They are essential for identifying spatial disparities in carbon emissions and designing tailored low-carbon strategies [16].

Therefore, this study selects the Beijing-Tianjin-Hebei region as a case study. By taking county-level administrative units as the analytical scale, it investigates the spatiotemporal relationships and inherent driving factors between land use carbon emissions and ESV. The findings are expected to provide scientific evidence for coordinated regional emission reduction and land use spatial planning. Moreover, the findings have broader relevance beyond the case region. The identified development challenges and transformation pathways are typical of other urban agglomerations in China and similar regions globally. The conclusions offer both theoretical insights and practical guidance for other regions in China and developing countries facing similar pressures.

2. Literature Review

In recent years, the spatiotemporal interactions between land use carbon emissions and ESV have received increasing attention from the academic community. Existing studies generally agree that land use change is not only a major source of carbon emissions but also a key factor influencing the structure and function of ecosystems [17,18]. The expansion of construction land is often accompanied by a reduction in ecological land types such as cropland and forest, thereby weakening regional carbon sink capacity and lowering ESV levels. Meanwhile, some regions have achieved synergistic effects in reducing emissions and enhancing ESV through land consolidation, ecological restoration, and “carbon sequestration–emission reduction” policies. Therefore, balancing economic growth with low-carbon development while maintaining ecosystem services has become a critical issue at the intersection of land use and ecosystem research. This paper provides a systematic review of existing literature from three perspectives: methods for accounting land use carbon emissions and ESV, their spatiotemporal patterns, and the mechanisms through which key influencing factors shape their interactions.

2.1. Accounting Methods

Due to the high uncertainty of natural ecological processes and the complexity of socio-economic activities, there is still no unified methodological framework for accounting land use carbon emissions. Moreover, the accuracy of existing methods remains to be improved. Currently, the commonly used methods can be broadly classified into two categories: bottom-up approaches, which are based on natural ecosystems, and top-down approaches, which are based on socio-economic systems [19]. The bottom-up methods include model simulation, field surveys, and remote sensing estimation [20,21]. Top-down methods encompass carbon emission coefficient methods, direct measurements, and factor decomposition techniques [22,23]. Among them, the carbon emission coefficient method has been widely applied in land use carbon

emission studies due to its data accessibility and ease of calculation. The *2006 IPCC Guidelines for National Greenhouse Gas Inventories* and the *Guidelines for Compiling Provincial Greenhouse Gas Inventories* are prominent examples of its practical application.

Extensive research has also been conducted on the evaluation of ESV. Initially, Costanza et al. [24] proposed the equivalent value method based on utility and equilibrium value theories. They also estimated the global economic value of ecosystem services. This method has since become the mainstream approach for global ESV assessment. However, because of environmental heterogeneity and ESV evaluation complexity, region-specific adjustments are needed to improve estimation accuracy. In response, Xie et al. [25], building on Costanza's work, developed an ESV equivalent coefficient table tailored to China's ecological conditions. The table was revised in 2015 by Xie et al. [26] and has since been widely used by Chinese scholars to analyze ESV's spatiotemporal variations across regions.

2.2. Spatiotemporal Patterns

Accurate identification of the dynamic evolution and spatial heterogeneity of land use carbon emissions and ESV is essential. This understanding helps reveal their general patterns of change and differentiation.

Previous studies on the spatiotemporal patterns of land use carbon emissions have employed diverse perspectives, data sources, and methods. These approaches have gradually evolved over time. Regarding research perspectives, scholars have studied carbon emission characteristics, including ecological and economic carrying coefficients [27]. They have also explored the coupling relationships between land use carbon emissions and various socio-economic factors, such as population and economic development [28,29]. There is a clear trend from single-dimensional to multidimensional integrated analyses. Concerning data sources, most studies rely on statistical and census data related to land use and energy consumption, while some use remote sensing and geospatial data [30]. Overall, the trend has shifted from relying on single-source data to integrating multi-source data from "sky-space-ground" systems. This integration leverages the strengths of each dataset, enabling a more comprehensive understanding of the evolution and spatial differentiation of land use carbon emissions [23,31]. Methodologically, research has progressed from basic correlation and spatial statistical analyses, such as spatial clustering and hotspot analysis, to more complex system modeling methods like system dynamics. Network-based approaches, including ecological network analysis, have also been increasingly adopted. This reflects a shift from single-method studies to integrated multi-method frameworks [29,32].

ESV is influenced by both natural factors and human activities. It exhibits phased variations along with significant spatial clustering and gradient differences. Unlike traditional static assessments, spatiotemporal pattern analysis captures ESV's dynamic evolution. It helps identify key transitional periods and sensitive areas, providing targeted evidence for differentiated management and regulation. In recent years, researchers have integrated multi-source data such as land use, remote sensing, socio-economic statistics, and field surveys. They have applied methods like the value equivalent method and the InVEST model [33,34]. Based on parameter localization, studies have been conducted across multiple spatial scales, including global, national, regional, and watershed levels, yielding substantial insights [35,36]. However, challenges remain in current ESV spatiotemporal research, including scale transformation difficulties, model uncertainties, and data heterogeneity.

2.3. Influencing Factors

Investigating the influencing factors of land use carbon emissions and ESV is essential. It helps uncover the nature of spatial pattern changes and formulate precise regulatory strategies. The evolution and differentiation of both elements reflect spatial expressions of region-specific

resource endowments, environmental changes, and socio-economic dynamics. These patterns are driven by the coupled effects of natural and human factors.

For land use carbon emissions, natural drivers include climate [37], soil [38], and vegetation [39]. Human-related drivers cover energy structure [40], economic development [41], and urbanization [42]. Similarly, the spatiotemporal evolution of ESV is influenced by natural factors, including climate, hydrology, and ecosystem type and structure [43]. Human factors such as economic activity, population dynamics, policy interventions, and land use changes also play important roles [44]. Due to the combined influence of these factors, the internal mechanisms behind the evolution and differentiation of land use carbon emissions and ESV are complex and not yet fully understood.

In summary, although numerous studies have examined land use carbon emissions or ESV independently, few have integrated both into a common interaction framework. Furthermore, existing research has yet to fully explore the underlying mechanisms of the spatiotemporal interaction between land use carbon emissions and ESV. And some key aspects like spatiotemporal linkages, spatial clustering patterns, and driving factors still require systematic study.

3. Materials and Methods

3.1. Study Area Overview

The Beijing-Tianjin-Hebei region is located in the northern part of the North China Plain ($113^{\circ}27'–119^{\circ}50'$ E, $36^{\circ}05'–42^{\circ}40'$ N). As shown in Figure 1, its administrative divisions include Beijing Municipality, Tianjin Municipality, and Hebei Province, which comprises 11 prefecture-level cities: Shijiazhuang, Hengshui, Xingtai, Handan, Baoding, Langfang, Cangzhou, Zhangjiakou, Chengde, Qinhuangdao, and Tangshan. In 2024, the GDP of the Beijing-Tianjin-Hebei region was estimated at CNY 11.5 trillion. This accounts for approximately 8.53% of the national total and positions the region as a critical economic growth pole in China. Transformations among land use types during land use processes not only influence carbon emission levels but also alter the ESV. Due to its complex land use structure, rapid urbanization, and high energy consumption, the Beijing-Tianjin-Hebei region has become a major contributor to carbon emissions in China. It is estimated to contribute approximately 11% of national carbon emissions, with a carbon emission intensity approximately 40% higher than the national average. The region also possesses abundant ecosystem resources and has been designated as a demonstration zone for ecological restoration and environmental enhancement in China. However, substantial challenges remain in advancing these efforts.

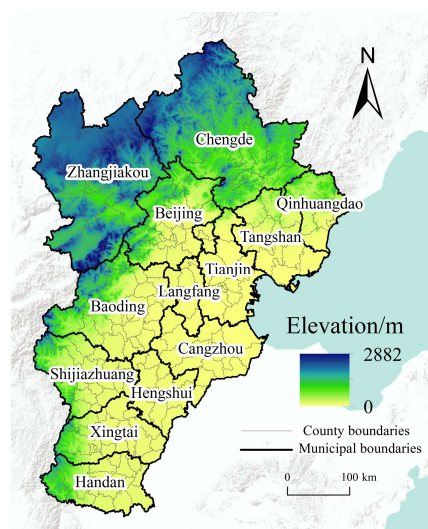


Figure 1. Overview of the research area.

3.2. Data Sources and Descriptions

As shown in Table 1, this is the source and description of the data used in this study.

Table 1. Data sources and descriptions.

Data Type	Data Source	Resolution
Land use data	Resource and Environment Science and Data Center, Chinese Academy of Sciences. (https://www.resdc.cn/ , accessed on 13 January 2025)	30 m
Digital elevation model data	Resource and Environment Science and Data Center, Chinese Academy of Sciences. (https://www.resdc.cn/ , accessed on 15 January 2025)	500 m
Nighttime light imagery data	Develop improved time-series DMSP-OLS-like data (1992–2019) in China by integrating DMSP-OLS and SNPP-VIIRS published by Wu et al. [45].	1 km
Average precipitation data	4 km daily gridded meteorological dataset for China (2000–2020) published by Zhang et al. [46].	1 km
Average temperature data	4 km daily gridded meteorological dataset for China (2000–2020) published by Zhang et al. [46].	1 km
Normalized difference vegetation index data	MOD13A3 dataset regularly released by NASA (https://www.earthdata.nasa.gov/ , accessed on 20 January 2025)	1 km
GDP data	Spatial distribution of GDP in kilometer grid in China published by Xu X L [47].	1 km
Population data	LandScan population dataset developed by the Oak Ridge National Laboratory (ORNL), USA (https://landscan.ornl.gov/ , accessed on 22 January 2025)	1 km
Energy consumption and socioeconomic data	Statistical materials including Beijing Statistical Yearbook, Tianjin Statistical Yearbook, Hebei Statistical Yearbook, China Statistical Yearbook, China Energy Statistical Yearbook, China Urban Statistical Yearbook, China County Statistical Yearbook, and National Compilation of Agricultural Product Cost and Benefit Data	None

3.3. Research Methods

The methodological framework employed in this study is presented in Figure 2. This study used land use data from five time points (2000, 2005, 2010, 2015, and 2020) to estimate carbon emissions from land use at the county scale in the Beijing-Tianjin-Hebei region. The estimation integrated the carbon emission coefficient method with the nighttime light inversion method. The ESV was calculated per unit area using the value equivalent factor method. To examine the spatiotemporal correlation between land use carbon emissions and ESV, a bivariate spatial autocorrelation analysis was conducted. Subsequently, a multinomial logit regression model was applied. This model identified the driving factors influencing the spatiotemporal interactions between the two variables.

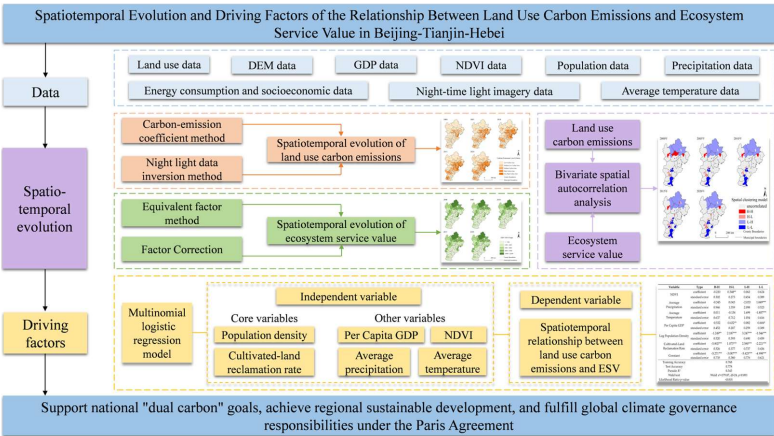


Figure 2. Research methodology flow chart. Note: The colors in this picture are only for aesthetic purposes and have no other implications.

3.3.1. Land Use Carbon Emission Accounting

Carbon emissions from land use were estimated using the emission coefficient method [48,49]. This approach follows guidelines recommended by the Intergovernmental Panel on Climate Change (IPCC, 2006; 2019) and has been adapted to China's context in numerous empirical studies [50,51]. Specifically, each land use type was assigned a carbon emission or sequestration coefficient based on its ecological function and anthropogenic intensity. The methodology of this study was based on these research findings and considered the actual land use conditions in the Beijing-Tianjin-Hebei region [48,49,51,52].

In this context, the carbon emission coefficient method was applied to calculate land use carbon emissions. The carbon emission coefficients corresponding to different land use types are shown in Table 2. Specifically, carbon emissions from cultivated land, forest land, grassland, water area, and unused land were estimated using a direct calculation method, whereas emissions from construction land were estimated using an indirect method.

(1) Direct Calculation Method

$$CA_x = \sum C_i = \sum S_i \times \alpha_i \quad (1)$$

In the formula, CA_x represents the direct carbon emissions of the x -th administrative region; C_i , S_i , and α_i represent the carbon emissions, area, and carbon emission coefficient of the i -th land use type, respectively.

Table 2. Carbon Emission Coefficients by Land Use Type.

Land Use Type	Cultivated Land	Forest Land	Grassland	Water Area	Unused Land
Carbon Emission Coefficient	0.4220	−0.6125	−0.0210	−0.2570	−0.0050

(2) Indirect Calculation Method

Ten major energy types were considered in this study, including coal, coke, crude oil, gasoline, kerosene, diesel oil, fuel oil, natural gas, and liquefied petroleum gas. Carbon emissions from construction land were calculated using standard coal conversion coefficients along with the corresponding carbon emission coefficients (Table 3). Due to the unavailability of energy consumption data at the county scale, nighttime light data were employed as a proxy indicator. This approach assumes that light intensity is strongly associated with regional economic activity and, consequently, with construction land carbon emissions [53,54].

Table 3. Standard coal conversion and carbon emission coefficients by energy type.

Energy Type	Standard Coal Equivalent Conversion Coefficient	Carbon Emission Coefficient
Coal	0.7143	0.7559
Coke	0.9714	0.8550
Crude oil	1.4286	0.5857
Gasoline	1.4714	0.5538
Kerosene	1.4714	0.5714
Diesel oil	1.4571	0.5921
Fuel oil	1.4286	0.6185
Natural gas	1.7143	0.5042
Liquefied petroleum gas	1.2280	0.5857
Electricity	0.1229	0.2132

As shown in Table 4, a regression analysis was conducted between total nighttime light intensity and carbon emissions across municipal areas in the Beijing-Tianjin-Hebei region. In Table 4, X and Y represent the total value of nighttime light brightness and carbon emissions from construction land, respectively. The resulting regression equations demonstrated strong fits ($R^2 > 0.70$), suggesting high model reliability for estimating energy consumption and carbon emissions at the municipal scale. Using the derived equations and nighttime light data at the county scale, carbon emissions from construction land were further estimated for the Beijing-Tianjin-Hebei region.

Table 4. Fitted equations for energy consumption carbon emissions by prefecture-level city in the Beijing-Tianjin-Hebei Region.

Municipal City	Formula	R^2
Beijing	$y = -0.0005x^2 + 245.0611x - 16,916,588.6491$	0.8869
Tianjin	$y = -0.0002x^2 + 149.1004x - 7,493,031.0201$	0.9444
Chengde	$y = -0.0020x^2 + 259.9574x - 2,148,350.7816$	0.9988
Zhangjiakou	$y = -0.0016x^2 + 267.0448x - 5,210,130.8110$	0.9951
Qinhuangdao	$y = -0.0018x^2 + 244.0938x - 2,522,723.2601$	0.9728
Tangshan	$y = -0.0009x^2 + 429.0482x - 22,497,599.4943$	0.9936
Baoding	$y = -0.0008x^2 + 316.9759x - 16,136,662.4999$	0.9986
Langfang	$y = 1.2083x^{1.3460}$	0.9269
Cangzhou	$y = -0.0019x^2 + 636.8169x - 37,021,465.6978$	0.9743
Shijiazhuang	$y = 0.0046x + 41,811.6055$	0.7055
Hengshui	$y = -0.0036x^2 + 485.1271x - 10,015,174.2472$	0.7302
Xingtai	$y = -0.0017x^2 + 405.5922x - 14,880,042.3515$	0.7322
Handan	$y = -0.0029x^2 + 793.7881x - 39,702,839.1399$	0.9664

$$CB_x = \sum_{i=1}^n e_i \times \beta_i \times \gamma_i \quad (2)$$

In the formula, CB_x , e_i , β_i , and γ_i represent the carbon emissions for the x -th city's construction land, the total energy consumption for the i -th energy type, the standard coal conversion coefficient, and the carbon emission coefficient, respectively.

(3) Calculation of Total Land Use Carbon Emissions

$$CT_x = CA_x + CB_x \quad (3)$$

In the formula, CT_x represents the total land use carbon emissions of the x -th administrative region.

3.3.2. ESV Calculation

ESV was estimated using the equivalent factor method, originally developed by Costanza et al. [24] and later refined by Xie et al. [55–57]. This method assigns standardized value coefficients to different land use types based on their ecological functions. To enhance regional accuracy, we adjusted the coefficients using local grain yield and market price data for the Beijing-Tianjin-Hebei region [58,59]. This method has been widely applied in large-scale ecological valuation studies in China and remains a transparent, consistent tool for comparing spatial patterns. The total ESV for each county was estimated by multiplying the area of each land use type by its corresponding ESV coefficient. The specific steps are as follows:

(1) Adjustment of Economic Value per Hectare of Grain Yield

One ESV equivalent corresponds to one-seventh of the average annual economic value of natural grain yield per hectare of cultivated land [25,26]. Considering the ecological and agricultural conditions of the region, three major crops—rice, wheat, and maize—were

selected. Their sown area, yield, and market prices were used as the baseline. To reduce the effects of price fluctuations, grain prices from 2000, 2005, 2010, and 2015 were adjusted to 2020 levels using the Consumer Price Index (CPI). Based on this adjustment, the economic value of grain yield was estimated to be CNY 1706.05 per hectare. The ESV coefficients for the region were subsequently derived (Table 5).

Table 5. ESV coefficients in the Beijing-Tianjin-Hebei region.

Ecosystem Services		Cultivated Land	Forest Land	Grass-Land	Water Area	Construction Land	Unused Land
Provisioning Services	Food Production	1885.18	430.78	398.08	1117.46	0	8.53
	Raw Material Production	417.98	989.51	585.74	622.71	0	25.59
	Water Supply	−2226.39	511.81	324.15	9280.91	0	17.06
Regulating Services	Gas Regulation	1518.38	3254.29	2058.63	2277.58	0	110.89
	Climate Regulation	793.31	9737.27	5442.30	5024.31	0	85.30
	Environmental Purification	230.32	2853.37	1797.04	7805.17	0	349.74
	Hydrological Regulation	2550.54	6372.09	3986.47	107,882.00	0	204.73
Supporting Services	Soil Conservation	887.15	3962.30	2507.89	2763.80	0	127.95
	Nutrient Cycling	264.44	302.82	193.35	213.26	0	8.53
	Biodiversity Maintenance	290.03	3608.29	2280.42	8888.51	0	119.42
Cultural Services	Aesthetic Landscape	127.95	1582.36	1006.57	5647.02	0	51.18
Total		6738.89	33,604.89	20,580.63	151,522.70	0	1108.93

(2) ESV accounting of counties in the Beijing-Tianjin-Hebei region

$$ESV = \sum_{i=1}^n S_{ij} \times E_r \quad (4)$$

In the formula, S_{ij} represents the area of the i -th land use type in county j , and E_r represents the adjusted ESV coefficient.

3.3.3. Bivariate Spatial Autocorrelation Analysis of Land Use Carbon Emissions and ESV

GeoDa software was used to analyze spatial clustering and dispersion patterns between land use carbon emissions and ESV using both Global Moran's I and Local Moran's I indices. Spatial relationships were visualized through bivariate LISA cluster maps. Clustering patterns were classified into four categories: High-High (H-H), High-Low (H-L), Low-High (L-H), and Low-Low (L-L). The model calculation formulas are as follows:

$$I = \frac{\sum_{i=1}^n \sum_{j=1}^n w_{ij} (x_i - \bar{x})(x_j - \bar{x})}{S^2 \sum_{i=1}^n \sum_{j=1}^n w_{ij}} \quad (5)$$

$$I_i = (x_i - \bar{x}) \sum_{j=1}^n w_{ij} (x_j - \bar{x}) / S^2 \quad (6)$$

In the formula, I and I_i represent the Bivariate Global Moran's I and Bivariate Local Moran's I indices, respectively; n represents the number of counties in the study area; W_{ij} is the $n \times n$ spatial weight matrix; x_i and x_j represent the attribute values of counties i and j ; and $\bar{x}$ and S^2 are the mean and variance of the attribute values.

3.3.4. Multinomial Logistic Regression Model

The spatiotemporal relationship between land use carbon emissions and ESV is influenced by many factors. The above factors can be summarized as socio-economic factors including population, economic development level, and natural environmental factors covering temperature, precipitation, and NDVI. However, selecting too many influencing factors can easily lead to multicollinearity problems. To this end, fully referred to the existing research results [60–62], and combined with the specific conditions of the study area, this study employed stepwise regression to screen out the dominant drivers, and then the six factors with a higher degree of explanation were incorporated into the model. These factors include NDVI, average precipitation, average temperature, per capita GDP, population density, and cultivated land reclamation rate. Their meanings are, respectively, county-level average NDVI, county-level annual average precipitation/mm, county-level annual average temperature/ $^{\circ}\text{C}$, per capita GDP/CNY 10,000·person $^{-1}$, logarithm of the density of permanent population distribution at the county level/person·km $^{-2}$, and proportion of cultivated land area to total area of administrative unit/%. Taking the uncorrelated areas in LISA agglomeration as a reference, a multinomial logit model was employed to explore the driving forces behind the spatial relationships between land use carbon emissions and ESV. The model specification is given in Formula (7).

Due to the extremely high population densities in Beijing and Tianjin, which created outliers in the data, a logarithmic transformation was applied to the population density variable. Logarithmic transformation is a common statistical treatment based on the overall distribution characteristics of population density, the inherent laws of variables, and the need for model robustness. This transformation does not merely handle individual extreme values but also addresses skewness in the overall data distribution. It reduces the impact of extreme values, makes the data closer to a normal distribution, and helps meet regression assumptions. It is applicable to the population density of the entire study area. Furthermore, variance inflation factor (VIF) tests showed that all factors had VIF values below 5, indicating no multicollinearity among the variables (Table 6).

Table 6. VIF for each factor.

Driving Factors	NDVI	Average Precipitation	Average Temperature	Per Capita GDP	Log Population Density	Cultivated-Land Reclamation Rate
VIF	1.601	4.309	4.344	1.148	2.602	1.668

$$\ln(P(Y = k)/P(Y = 0)) = \beta_0^k + \beta_1^k X_1 + \beta_2^k X_2 + \cdots + \beta_i^k X_i \text{ for } k = 1, \dots, 4. \quad (7)$$

In the formula, Y is the dependent variable representing the LISA clustering patterns, with values $k = 0, 1, 2, 3, 4$. Here, $k = 0, 1, 2, 3, 4$ correspond to non-significant clustering, H-H clustering, L-L clustering, H-L clustering, and L-H clustering patterns, respectively, with $k = 0$ designated as the reference category; $X_1, X_2, \dots, X_p$ are independent variables representing factors such as NDVI, average precipitation, average temperature, etc. $P(Y = k)$ denotes the probability of the dependent variable belonging to the k -th category; β_0^k is the intercept term for the k -th category; and β_i^k represents the regression coefficient of the independent variable X_i for the k -th category relative to the reference category $Y = 0$.

4. Results

4.1. Spatiotemporal Patterns of Land Use Carbon Emissions

From 2000 to 2020, land use carbon emissions in the Beijing-Tianjin-Hebei region showed an overall increase followed by a minor decline (Table 7). Between 2000 and 2015, emissions rose from 71.86 million tons to 164.61 million tons—an increase of 129.08%. However, from 2015 to 2020, emissions declined slightly to 159.70 million tons, reflecting a reduction of 2.98%. Throughout the study period, construction land was consistently the dominant contributor to carbon emissions, accounting for 97.62% to 99.24% of the total. In contrast, a steady decline was observed in emissions from cultivated land, with its share dropping from 6.69% to 2.70%. Meanwhile, land use-related carbon sequestration exhibited a modest increase. It rose from 2.97 million tons in 2000 to 3.03 million tons in 2020, representing an overall growth of 2.05%. Forest land, grassland, and water areas were identified as the primary contributors to carbon sequestration, accounting for approximately 92–93%, 2–3%, and 5–6%, respectively. Large-scale ecological restoration projects were implemented, including wetland rehabilitation in Binhai New Area, ecological reconstruction in the mining zone of eastern Sanhe City, and ecological management initiatives in Baiyangdian Lake. These projects significantly enhanced vegetation coverage. These efforts played an essential role in increasing the region’s carbon sink capacity during the study period.

Table 7. Carbon emissions from land use in the Beijing-Tianjin-Hebei region by category $\times 10^4$ /t.

Year	Type	Carbon Source			Carbon Sink			Net Carbon Emissions
		Cultivated Land	Construction Land	Forest Land	Grass-Land	Water Area	Unused Land	
2000	Carbon Emissions / 10^4 /t	460.96	6724.82	−272.76	−7.40	−16.53	−0.10	6889.00
	Proportion/%	6.69%	97.62%	−3.96%	−0.11%	−0.24%	<0.01%	100%
2005	Carbon Emissions / 10^4 /t	456.61	11,521.86	−272.78	−7.36	−16.02	−0.10	11,682.21
	Proportion/%	3.91%	98.63%	−2.34%	−0.06%	−0.14%	<0.01%	100%
2010	Carbon Emissions / 10^4 /t	454.62	15,051.93	−272.74	−7.34	−15.94	−0.10	15,210.43
	Proportion/%	2.99%	98.96%	−1.79%	−0.05%	−0.10%	<0.01%	100%
2015	Carbon Emissions / 10^4 /t	428.82	16,032.32	−277.38	−7.19	−17.09	−0.08	16,159.40
	Proportion/%	2.65%	99.21%	−1.72%	−0.04%	−0.11%	<0.01%	100%
2020	Carbon Emissions / 10^4 /t	422.36	15,547.50	−277.71	−7.10	−18.05	−0.08	15,666.91
	Proportion/%	2.70%	99.24%	−1.77%	−0.05%	−0.12%	<0.01%	100%

To facilitate visual interpretation, land use carbon emissions in the Beijing-Tianjin-Hebei region were classified into five tiers using the natural breaks method, based on existing studies and regional characteristics [63,64]: low-emission areas (<0.5 million tons), medium-low-emission areas (0.5–0.8 million tons), medium-emission areas (0.8–1.5 million tons),

high-emission areas (1.5–2.2 million tons), and ultra-high-emission areas (2.2–5.5 million tons), as shown in Figure 3.

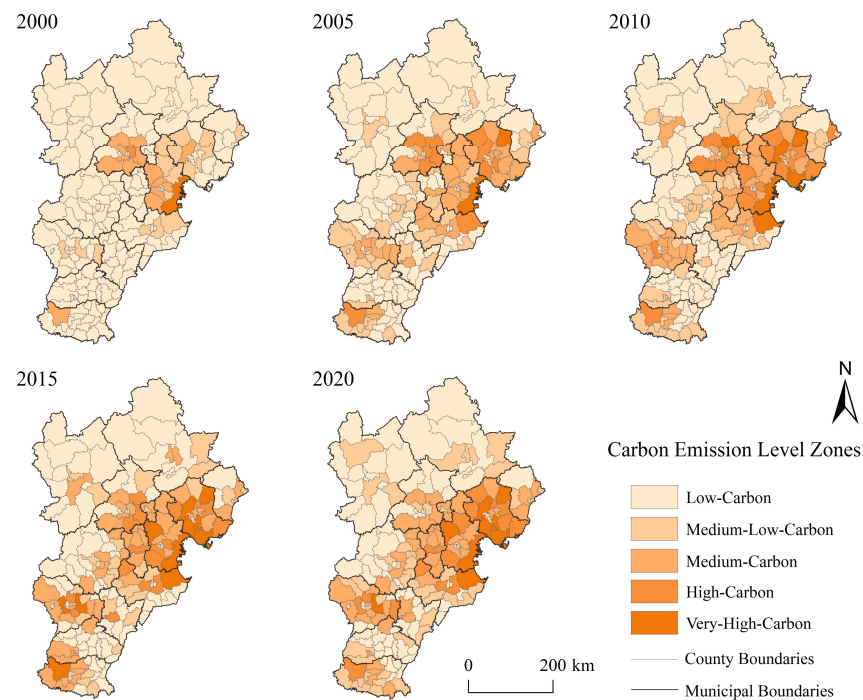


Figure 3. Spatiotemporal patterns of carbon emissions from land use at the county scale in Beijing-Tianjin-Hebei.

As shown in Figure 3, emissions exhibit strong spatial heterogeneity. High-emission areas are primarily concentrated in urban and industrial hubs such as Binhai New Area in Tianjin, Qian'an and Fengnan in Tangshan, and Gaocheng in Shijiazhuang. These zones belong to the Bohai Rim Economic Belt and provincial capital metropolitan areas, where energy-intensive industries dominate, and fossil fuels remain the primary energy source. For instance, Binhai New Area, formed through the merger of three industrial districts, recorded emissions as high as 4.60 million tons in 2020.

In contrast, low-emission zones are generally located in the northwestern ecological conservation region, including Longhua, Fengning, and Weichang in Chengde, as well as Chicheng in Zhangjiakou. These areas feature extensive forest and grassland coverage, limited industrial activity, and strong ecological functions. Chengde and Zhangjiakou also play key roles in regional carbon sink capacity through national ecological projects such as sandstorm source control and wetland conservation. Additionally, Qinhuangdao benefits from coastal carbon sink resources, with Haigang district maintaining relatively stable carbon sequestration. The COVID-19 pandemic in 2020 contributed to a temporary drop in emissions in several medium- and high-emission counties. This decline was due to lockdowns and reduced industrial activity.

Overall, the spatial distribution of carbon emissions in the Beijing-Tianjin-Hebei region reflects a pronounced contrast between urban-industrial zones and ecological-agricultural areas. This pattern underscores the necessity of differentiated carbon management strategies. These include promoting industrial upgrading in high-emission zones and strengthening ecological protection in low-emission regions to support balanced regional development under China's dual carbon targets.

4.2. Spatiotemporal Patterns of ESV

From 2000 to 2020, the ESV in the Beijing-Tianjin-Hebei region first declined and then increased (Table 8). Despite these changes, it remained generally stable, with only minor fluctuations. Specifically, between 2000 and 2010, the ESV declined from CNY 393,420.71 million to CNY 388,366.19 million, indicating a decrease of 1.28%. From 2010 to 2020, it increased to CNY 396,013.90 million, corresponding to a growth rate of 1.97%. Forest land and water areas were the primary contributors to ESV, accounting for over 38% and 24%, respectively, both of which exhibited a slight upward trend in their contribution rates. In contrast, the contribution rates of cultivated land and grassland ranged between 17% and 19%, with a slight downward trend observed over the study period.

Table 8. ESV statistics by category in the Beijing-Tianjin-Hebei region.

Year	Type	Cultivated Land	Forest Land	Grass-Land	Water Area	Construction Land	Unused Land	Total Value
2000	Value/10 ⁶ CNY Proportion/%	73,611.14 18.71	149,651.01 38.04	72,477.95 18.42	97,450.44 24.77	0.00 0.00	230.16 0.06	393,420.71 100
2005	Value/10 ⁶ CNY Proportion/%	72,915.93 18.73	149,659.13 38.43	72,115.02 18.52	94,463.83 24.26	0.00 0.00	223.74 0.06	389,377.65 100
2010	Value/10 ⁶ CNY Proportion/%	72,597.51 18.70	149,638.60 38.53	71,928.71 18.52	93,981.81 24.20	0.00 0.00	219.56 0.06	388,366.19 100
2015	Value/10 ⁶ CNY Proportion/%	68,477.77 17.47	152,183.23 38.82	70,457.48 17.97	100,750.60 25.70	0.00 0.00	183.53 0.05	392,052.60 100
2020	Value/10 ⁶ CNY Proportion/%	67,445.78 17.03	152,365.56 38.47	69,589.45 17.57	106,427.25 26.88	0.00 0.00	185.85 0.05	396,013.90 100

The spatial differentiation of ESV in the Beijing-Tianjin-Hebei region is significant (Figure 4), with high-value clusters primarily distributed in the northwestern ecological conservation area and the eastern coastal zone. This pattern is closely related to factors such as complex topography, vertical vegetation stratification, rich biodiversity, and a strong reliance on natural ecosystems. In contrast, the central functional core and southern expansion areas exhibit lower ESV, mainly due to intensive land use, low ecological heterogeneity, and high population densities. Counties such as Weichang, Fengning, and Longhua in Chengde consistently recorded the highest ESV during the study period. This is due to their stable land use patterns, extensive forest and grassland coverage, and their critical location within the Yanshan ecological security barrier. Binhai New Area in Tianjin also maintained relatively high ESV. This is attributed to well-preserved wetland and marine ecosystems along the Bohai Bay, supported by strong local investment in ecological protection.

Overall, the spatial variation in ESV reflects a clear ecological-developmental gradient, shaped by both natural endowments and land use intensity. Moreover, the implementation of regional ecological spatial frameworks has contributed to the conservation and enhancement of ESV in key ecological zones. These frameworks include the “two mountains, two wings, three belts, multiple corridors, and multiple centers” strategy. This highlights the importance of integrating ecological zoning with land planning to ensure balanced regional development and ecosystem service sustainability.

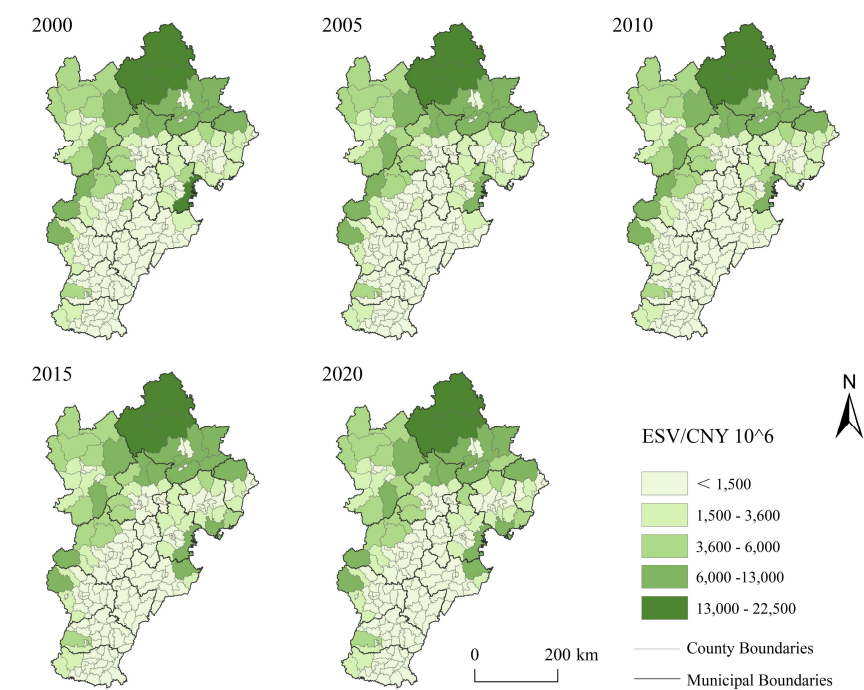


Figure 4. Spatiotemporal patterns of ESV at the county scale in Beijing-Tianjin-Hebei.

4.3. Spatial Autocorrelation Analysis

As shown in Table 9, Global Moran’s *I* values remained consistently negative, with *p*-values below 0.05. This indicates a statistically significant negative spatial correlation between land use carbon emissions and ESV in the Beijing-Tianjin-Hebei Region. Specifically, increases in land use carbon emissions were associated with decreases in ESV. Furthermore, from 2000 to 2020, Global Moran’s *I* exhibited an overall increasing trend. This indicates a transition from spatial clustering to spatial dispersion in the relationship between carbon emissions and ESV. This trend suggests enhanced spatial coordination between regional ecological protection and carbon management strategies.

Table 9. Bivariate Global Moran’s *I* for Beijing-Tianjin-Hebei counties.

Spatial Statistic	2000	2005	2010	2015	2020
Global Moran’s <i>I</i>	−0.100	−0.101	−0.048	−0.051	−0.052
<i>p</i>	0.001	0.001	0.046	0.042	0.031
<i>Z</i>	−3.126	−3.290	−1.987	−1.995	−2.011

From 2000 to 2020, the dominant bivariate clustering patterns between land use carbon emissions and ESV were identified as L-H and L-L clusters, which were primarily concentrated in the northern and central-southern parts of the region, respectively. In contrast, H-H and H-L clusters appeared sparsely distributed and exhibited spatial fragmentation (Figure 5).

L-L clusters are mainly distributed in the central and southern plains of the region, particularly at the junctions of Shijiazhuang, Baoding, Cangzhou, and Hengshui—such as in counties like Anguo, Lixian, and Raoyang. These areas are dominated by agricultural and ecological land with minimal construction development, resulting in relatively stable but low levels of both carbon emissions and ESV. Their industrial structure is primarily based on traditional agriculture and small-scale processing, lacking both high-emission industries and high-value ecological sectors. Additionally, the absence of influential urban centers nearby contributes to weak economic linkages and slow land use

change. This pattern reflects the persistence of low-intensity land systems in economically peripheral areas.

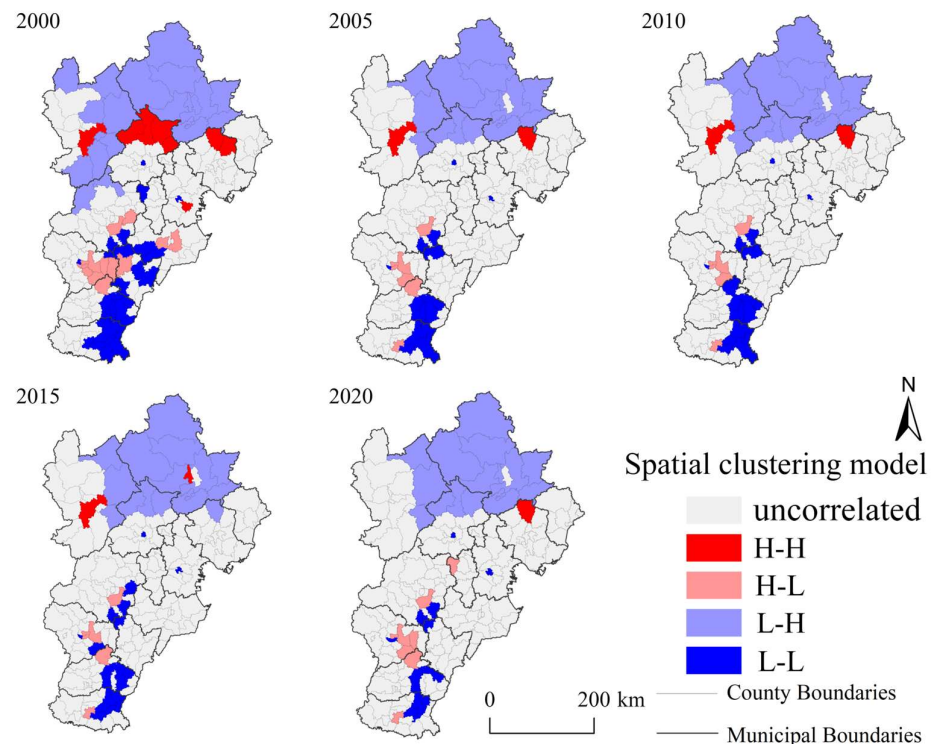


Figure 5. Bivariate LISA clustering of land use carbon emissions and ESV at the county scale in Beijing-Tianjin-Hebei.

H-H clusters are few in number, spatially fragmented, and have declined over time. Early clusters appeared in Beijing's mountainous districts and industrial hubs like Qian'an and Qianxi in Tangshan. The former gradually exited the H-H category due to limited construction expansion. In contrast, the latter retained their classification owing to the coexistence of intensive industry and favorable ecological conditions. These areas illustrate the spatial overlap of legacy industries and high ecological endowments, forming unique dual-high zones.

H-L clusters are found in urban–rural transition zones such as Ningjin in Xingtai and Qingyuan in Baoding. These areas exhibit high carbon emissions due to expanding industrial activities and land conversion. However, they lack corresponding ecological compensation, resulting in declining ESV. This mismatch highlights the ecological cost of rapid urban expansion without sustainable land use planning.

L-H clusters are concentrated in ecologically rich areas like Guyuan, Huailai, and Chicheng, where forest and grassland dominate and industrial activity is minimal. Low carbon emissions combined with strong ecological function support their classification as L-H clusters. This reflects successful ecological conservation under limited development pressure.

Overall, the spatial patterns of LISA clusters reveal a landscape where ecological value and carbon intensity are shaped by the interplay of land use structure, industrial development, and regional planning. Understanding these spatial dynamics is essential for designing differentiated land management and carbon reduction strategies across the region.

4.4. Multinomial Logit Regression Analysis

As shown in Table 10, the training accuracy was 0.768, and the test accuracy was 0.778, suggesting that the model exhibited stable generalization ability. The pseudo R^2 was 0.343; in the Wald test, Wald $\chi^2 = 179.87$, $df = 24$, $p < 0.001$; and in the likelihood ratio test, the LR p -value was less than 0.001. These results suggest that the model performed well and that the explanatory power of the variables was statistically significant. Overall, population density and the cultivated-land reclamation rate emerge as the core determinants shaping the spatial clustering patterns of carbon emissions and ESV. Meanwhile, average precipitation, average temperature, and per capita GDP exhibit differentiated effects across cluster types.

Table 10. Multinomial logit regression results ^{(1), (2)}.

Variable	Type	H-H	H-L	L-H	L-L
NDVI	Coefficient	−0.220	0.548 **	0.062	0.624
	Standard error	0.302	0.273	0.454	0.389
Average Precipitation	Coefficient	−0.345	0.043	−2.033	1.849 ***
	Standard error	0.946	1.359	2.098	0.523
Average Temperature	Coefficient	0.011	−0.134	1.699	−1.807 ***
	Standard error	0.637	0.712	1.054	0.416
Per Capita GDP	Coefficient	−0.532	−0.432 **	0.082	−0.606 *
	Standard error	0.452	0.207	0.259	0.309
Log Population Density	Coefficient	−1.249 **	2.187 ***	3.247 ***	−1.546 ***
	Standard error	0.520	0.395	0.690	0.459
Cultivated-Land Reclamation Rate	Coefficient	−1.802 ***	1.073 ***	2.580 ***	−2.221 ***
	Standard error	0.526	0.377	0.737	0.436
Constant	Coefficient	−5.271 ***	−3.087 ***	−5.425 ***	−4.998 ***
	Standard error	0.735	0.380	0.776	0.621
Training Accuracy			0.768		
Test Accuracy			0.778		
Pseudo R^2			0.343		
Wald test		Wald $\chi^2 = 179.87$, $df = 24$, $p < 0.001$			
Likelihood Ratio p -value			<0.001		

Note: ⁽¹⁾ * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$; ⁽²⁾ The uncorrelated areas serve as the reference category for the model.

Counties exhibiting H-H clustering patterns are characterized by concurrently high carbon emissions and high ESV. These areas reflect a synergy between socio-economic development and ecological conservation, aligning with the concept of “high-quality development”. Taking the uncorrelated areas as a reference, the primary drivers contributing to the formation of the H-H agglomeration areas of land use carbon emissions and ESV in the Beijing-Tianjin-Hebei region are population density (−1.249, $p < 0.05$) and cultivated-land reclamation rate (−1.802, $p < 0.01$), both of which demonstrate significant negative correlations. These findings suggest that excessive demographic pressure and intensive land use practices may compromise ecological performance. H-H counties are typically situated in ecologically favorable or peri-urban areas where population density and cultivation intensity remain moderate.

L-L clusters, marked by both low carbon emissions and low ESV, often represent underdeveloped regions where human and land resources are overexploited without corresponding economic or ecological benefits. In comparison to uncorrelated areas, the

main factors influencing the formation of L-L clusters include NDVI (0.548, $p < 0.05$), population density (2.187, $p < 0.01$), and land reclamation rate (1.073, $p < 0.01$), all of which exhibit significant positive correlations. Conversely, per capita GDP (-0.423 , $p < 0.05$) shows a negative association. These results indicate that high resource pressure combined with low economic output contribute to ecological inefficiency.

H-L clusters, characterized by high carbon emissions and low ESV, are commonly found in regions experiencing rapid industrial expansion or agricultural activity but lacking sufficient ecological infrastructure. Relative to uncorrelated areas, population density (3.247, $p < 0.01$) and reclamation rate (2.580, $p < 0.01$) are the primary positive drivers. Although other variables do not reach statistical significance, their direction trends suggest potential risks. Specifically, temperature exhibits a positive effect, while NDVI and per capita GDP show negative tendencies. This suggests additional risks from rising temperatures and economic intensification.

Conversely, L-H clusters exhibit relatively low carbon emissions but high ESV, and are typically located in ecologically sensitive or low-development intensity zones. With uncorrelated areas as a reference, average precipitation (1.849, $p < 0.01$) demonstrates a strong positive influence on ESV. In contrast, average temperature (-1.807 , $p < 0.01$), per capita GDP (-0.606 , $p < 0.1$), population density (-1.564 , $p < 0.01$), and land reclamation (-2.221 , $p < 0.01$) have significant negative effects. These findings suggest that cooler, wetter, and less densely populated environments are more conducive to generating ecological value, while unregulated economic growth may undermine ecological sustainability.

From a broader perspective, the spatial coupling of carbon emissions and ESV in the Beijing-Tianjin-Hebei region reflects common land use trade-offs observed in many developing regions globally. Rapid industrialization and population growth can amplify carbon emissions while degrading ecosystem services—particularly in areas with weak ecological infrastructure. Conversely, regions with natural advantages or robust conservation policies are more likely to achieve low-carbon, high-ESV outcomes.

5. Discussion

5.1. Comparison with Existing Studies

At present, limited studies have investigated land use carbon emissions and ESV within a two-factor interaction framework. Existing studies generally adopt a similar analytical approach: first employing bivariate spatial autocorrelation to explore their spatiotemporal relationship, followed by the application of additional methods to identify potential driving factors. Most findings from bivariate spatial autocorrelation reveal a significant negative correlation between land use carbon emissions and ESV, a result that aligns with the findings of this study. For example, Zhang et al. [14], Wang et al. [12], and Gao et al. [65] conducted case studies in the Guanzhong region, Nansi lake basin, and Shanxi province, respectively, and all found significant negative correlations between land use carbon emission and ESV. Lang et al. [62] and Zhao et al. [13] further combined Pearson correlation analysis to evaluate the strength of the linear relationship, and their results similarly confirmed a significant negative correlation. The results of this study are highly consistent with these previous findings. This not only validates the methodological soundness of our approach but also enhances both the internal validity and external generalizability of our conclusions. However, Zhou et al. [66], in a study conducted in the Zhoushan Islands, observed a strong positive correlation between ESV and carbon sequestration cost at the 99% confidence level. They attributed this discrepancy to the unique environmental characteristics of island regions, such as limited carrying capacity, low population density, constrained urban expansion, scarce freshwater resources, and fragile ecosystems.

Moreover, existing studies have not adequately explored the influencing factors of the spatiotemporal relationship between land use carbon emissions and ESV, and the underlying mechanisms remain insufficiently understood. These influencing factors vary across regions due to heterogeneous resource endowments, changes in the natural environment, and socio-economic activities. For instance, Chen et al. [11] conducted a study in the Yellow River Basin and found that, compared with “L-L” clusters, per capita GDP, energy efficiency, and precipitation were significantly negatively correlated with “H-H” and “H-L” clusters. In contrast, total population and land reclamation rate exhibited significant positive and negative correlations, respectively, with “L-H” clusters. Our findings indicate that, compared with non-significant regions, per capita GDP is negatively correlated with “H-L” and “L-L” clusters, which aligns with the results of Chen et al. Population density and land reclamation rate are negatively correlated with “H-H” and “L-L” clusters but positively correlated with “H-L” and “L-H” clusters. Meanwhile, mean temperature, precipitation, and per capita GDP are negatively correlated with “L-L” clusters. These results further underscore the importance of analyzing influencing factors after identifying the spatiotemporal relationship between land use carbon emissions and ESV. Region-specific policy recommendations derived from this analysis are both scientifically grounded and practically applicable, offering theoretical insights and empirical support for the coordinated governance of carbon reduction and ecological conservation.

5.2. Limitations and Future Directions

This study employed an improved equivalent factor method proposed by Xie. The equivalent factors were regionally adjusted according to the economic value of local grain yield to enhance the accuracy and regional applicability of ESV assessments. However, due to the Beijing-Tianjin-Hebei region's vast size and significant ecological heterogeneity, a uniform correction approach may fail to capture spatial variability fully. Future research could integrate multi-source ecological, climatic, and socio-economic data to develop a more adaptive and flexible localized correction system. This would improve the precision and representativeness of ESV evaluations. Additionally, combining scenario simulation with system dynamics modeling may provide deeper insights into the co-evolution mechanisms of land use carbon emissions and ecosystem services. This can help explore synergistic pathways for carbon reduction and ecological quality improvement. These efforts would provide empirical evidence and decision-making support for achieving China's dual carbon goals and advancing global ecological sustainability.

6. Conclusions

Land use carbon emissions in the Beijing-Tianjin-Hebei region followed a rising trend from 71.86 million tons in 2000 to a peak of 164.61 million tons in 2015, before declining to 159.70 million tons by 2020. Carbon emissions were predominantly generated from construction land, which contributed approximately 96.32%. In contrast, forest land accounted for 91.94% of the total carbon sequestration. High-emission counties were clustered around municipal cores (e.g., Beijing, Tianjin) and provincial capitals. In contrast, areas with high carbon sequestration were concentrated in the northwestern ecological zones (e.g., Zhangjiakou, Chengde).

From 2000 to 2020, ESV in the Beijing-Tianjin-Hebei region experienced an initial decline from CNY 393.42 billion in 2000 to CNY 388.37 billion in 2010, followed by a gradual increase to CNY 396.01 billion by 2020. The overall fluctuation was minor, and ESV remained relatively stable throughout the period. Forest and water bodies were consistently the largest contributors to total ESV, accounting for more than 38% and 24%, respectively. The northwestern ecological conservation zones and eastern coastal development zones

were identified as high-value clusters. In contrast, the central agricultural plains and southern urban agglomerations were characterized by relatively low ESV values. Cities such as Chengde, Zhangjiakou, and the Binhai New Area in Tianjin have sustained high ESV levels. This is largely attributable to favorable ecological endowments and continuous ecological restoration initiatives.

From 2000 to 2020, a negative spatial correlation was observed between land use carbon emissions and ESV in the Beijing-Tianjin-Hebei region, accompanied by a shift from clustering to dispersion. The bivariate LISA clustering patterns predominantly exhibit L-H and L-L clusters, which are primarily located in the northern and central-southern parts of the region. In contrast, H-H and H-L clusters appear infrequently and are more spatially dispersed;

Population density and cultivated-land reclamation rate have been identified as the most influential factors affecting carbon–ESV clustering patterns. High population density and intensive land reclamation tend to suppress both H-H and L-H clustering patterns. At the same time, they facilitate the emergence of two “carbon–ESV imbalance” modes: H-L and L-L. Average precipitation, average temperature, and per capita GDP exhibit varying effects across different clustering modes. Specifically, average precipitation has a significant positive effect on the formation of L-L clustering patterns. Average temperature has an inhibitory effect, while per capita GDP exerts significantly negative influences in both L-H and L-L modes.

7. Generality and Broader Implications

With global climate adaptation and ecological restoration advancing in tandem, optimizing land use structure, achieving low carbon emissions, and maintaining ESV have become key strategies to enhance ecological carrying capacity. Though focused on the Beijing-Tianjin-Hebei region, this study’s framework and policy insights are broadly applicable to other regions facing similar challenges in spatial governance and eco–carbon coordination.

Specifically, the dual-factor interaction framework is suitable not only for the Beijing-Tianjin-Hebei region but also for countries and regions facing rapid urbanization, land scarcity, and ecological degradation, including India, Vietnam, Indonesia, Nigeria, and parts of South America [67–69]. In these areas, the absence of effective ecological spatial regulation mechanisms often leads to a spatial mismatch characterized by “high carbon emissions–low ESV”, further intensifying ecological degradation and climate risks. By integrating both socio-economic and biophysical variables—such as population density, per capita GDP, cultivated-land reclamation rate, NDVI, precipitation, and temperature—this approach allows regions to identify spatial patterns and drivers of land use carbon emissions and ESV, designate high-priority regulatory units, implement ecological compensation, and establish priority zones for green infrastructure investment.

Furthermore, this study identifies spatial combinations like “high carbon emissions–low ESV” and “low carbon emissions–high ESV” through spatial interaction analysis. It proposes targeted, region-specific land use and ecological policies to enhance synergy between ecological protection and carbon reduction. For “high carbon emissions–low ESV” regions, measures include designating ecological protection redlines, strictly controlling new industrial land approvals, promoting energy-intensive industry transformation, and restoring idle land, for example through planting high carbon-sequestration vegetation and constructing urban wetland parks. Notably, regions with “low carbon emissions–high ESV” should establish long-term ecological compensation mechanisms and encourage low-carbon industries, such as eco-tourism and organic agriculture, to prevent overexploitation and consolidate ecological gains. Notably, the study also highlights the benefits

of wetland restoration and mine ecological rehabilitation on regional carbon sequestration and ecological value. These findings provide valuable insights for resource-exhausted or ecologically fragile regions globally, demonstrating the broader applicability of the dual-factor framework across diverse socio-economic and ecological contexts.

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Informed Consent Statement: All authors are aware of and agree to the content of this paper.

Data Availability Statement: Publicly available data sources are detailed in the Data Sources and Descriptions (Section 2.2) and can be accessed via the links provided in Table 1. Processed data used in this study are available from the corresponding author on reasonable request.

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Abbreviations

The following abbreviations are used in this manuscript:

H-H	High-high agglomeration areas
H-L	High-low agglomeration areas
L-H	Low-high agglomeration areas
L-L	Low-low agglomeration areas

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