



OPEN

Investigating spatio-temporal variations and contributing factors of land use-related carbon emissions in the Beijing-Tianjin-Hebei Region, China

Debao Yuan¹, Liuya Zhang^{1✉}, Yuqing Fan^{1,2} & Renxu Yang^{1,2}

The land use change is the primary factor in influencing the regional carbon emissions. Studying the effects of land use change on carbon emissions can provide supports for the development policies of carbon emission. Using land use and energy consumption data, this study measures carbon emissions from land use dynamics in the Beijing-Tianjin-Hebei region from 2000 to 2020. The standard deviation ellipse model is employed to investigate the distribution characteristics of the spatial patterns of carbon emissions, while the Geographically and Temporally Weighted Regression (GTWR) model is used to examine the contributing factors of carbon emissions and their spatial and temporal heterogeneity. Results indicate a consistently increasing trend in carbon emissions from land use in the Beijing-Tianjin-Hebei region from 2000 to 2020. Construction land is characterized with both the primary source and an increasing intensity of carbon emissions. Besides, the spatial distribution of carbon emissions from land use in the Beijing-Tianjin-Hebei region demonstrates an aggregation pattern from in the northeast-southwest direction towards the center, with a greater aggregation trend in the east-west direction compared to that in the south-north direction. During the study period, a positive correlation was documented between carbon emissions and factors including total population, economic development level, land use degree, and landscape patterns. This correlation showed a decreasing trend and reached a stable level at the end of the study period. Moreover, the analysis showed a negative correlation between industrial structure and carbon emissions, which showed an increasing trend and reached a relatively high level at the end of the study period.

Keywords Beijing-Tianjin-Hebei, Carbon emissions, Spatio-temporal heterogeneity, GTWR model

Carbon emissions are a significant contributor to global warming, and excessive emissions can seriously affect global environmental construction and sustainable human development. China is among the top rank of carbon emissions and it is estimated that the amount in China will peak by 2030. To take on the responsibility of energy conservation and emission reduction, the Chinese government has aimed to achieve carbon neutrality by 2060¹. Currently, China's economic development is heavily reliant on fossil fuels, making it difficult to transition to more sustainable energy sources in the short term². Additionally, China's carbon emissions are significant, with one-third of these emissions coming from land use, making it a major contributor to carbon emissions in the region^{3,4}. Terrestrial ecosystems are the largest carbon sinks. Improving their carbon sink capacity is widely recognized by the international community as one of the most economical ways to reduce greenhouse gases⁵. Therefore, it is significant to explore the spatial and temporal evolution of regional land-use carbon emissions and their influencing factors from a land-use perspective. This will promote the region's low-carbon transition and assist in achieving the goals of carbon peak attainment and carbon neutrality.

¹College of Geoscience and Surveying Engineering, China University of Mining and Technology, Beijing 100083, China. ²These authors contributed equally: Yuqing Fan and Renxu Yang. ✉email: SQT2200204094@student.cumtb.edu.cn

In recent years, scholars have conducted numerous studies on carbon emissions resulting from land use. These studies include accounting for land-use carbon emissions^{6,7}, analyzing spatial and temporal variations in land-use carbon emissions^{8,9}, and identifying the driving and influencing factors of land-use carbon emissions¹⁰. These studies cover various spatial scales, ranging from national to regional and even county levels^{11–13}. For instance, LUO Xiang et al. analyzed the spatial and temporal changes in cropland use efficiency across 11 provinces and cities in the Yangtze River Economic Belt in China from 2007 to 2016. They used cropland carbon emissions as a constraint for carbon emissions¹⁴. Yang and Liu analyzed the effect of land type transfer on carbon transfer in the Chang Zhu Tan urban agglomeration. The results indicate significant differences in the spatial distribution and direction of change of the regional carbon transfer effect within the urban agglomeration due to the influence of population growth, level of urbanization, and unbalanced economic development¹⁵. Duan et al. categorized the drivers of CO₂ emissions into six categories: population, fuel mix, energy intensity, production structure, consumption patterns, and consumption. They quantified the impact of these drivers on a global scale¹⁶. Various models were used to identify the factors that influenced carbon emissions, including the LMDI decomposition method¹⁷, the input–output model¹⁸, the STIRPAT model¹⁹, the Laspeyres index method²⁰ and heterogeneity analysis models^{21,22}. Among them, the heterogeneity analysis model describes the differences in the impact of drivers in different time and space through models such as GWR and GTWR in order to reflect the reality more scientifically^{23,24}. Houbo et al. investigated the impact of resident population, urban green space, industry, industrial agglomeration, and commercial and service housing area on carbon emissions in the metropolitan area and various districts and counties of Shanghai, using the GWR model. The results showed that industrial and industrial agglomeration, as well as urban green space area, are important factors influencing the total amount of carbon emissions, with significant spatial and temporal heterogeneity²⁵. The GWR model is only applicable to large sample cross-sectional data and cannot reflect temporal heterogeneity. For this reason, the GTWR model improves the GWR model by embedding a time factor, providing a more comprehensive analysis.

As an essential growth area of China's economy, the influence of land use change on carbon emissions in the Beijing-Tianjin-Hebei region has become increasingly prominent²⁶. Amidst rapid urbanization, the growth trend of carbon emissions is becoming more pronounced. Known studies have disclosed several key factors, encompassing GDP, land use structure, and population size, and pointed out the spatio-temporal heterogeneity of these influencing factors^{27–32}. Nevertheless, the in-depth exploration of geotemporal heterogeneity in the Beijing-Tianjin-Hebei region remains insufficient. In light of the potential role of landscape pattern change in reducing carbon emissions³³, this study not only focuses on traditional factors such as carbon emission, population, economic development level, and industrial structure but also incorporates the landscape pattern index “Interspersion and juxtaposition index (IJI)” as an analysis factor. This index can effectively quantify the spatial distribution and juxtaposition of patches in the landscape, thereby revealing more comprehensively the impact of spatial land use change on the spatio-temporal heterogeneity of carbon emissions.

Taking the Beijing-Tianjin-Hebei region as an example, based on land use and energy consumption data, this study detailed estimated the carbon emissions from land use in the region. By utilizing the Standard Deviation Ellipse (SDE) analysis method, we deeply explored the temporal and spatial distribution pattern and dynamic changes of carbon emissions. Further, through the application of the Geographically and Temporally Weighted Regression (GTWR) model, we reveal the spatial differences of the driving factors of carbon emissions in different regions of the Beijing-Tianjin-Hebei region, aiming to provide a solid scientific basis for achieving low-carbon land use, developing a low-carbon economy and formulating differentiated carbon neutrality strategies in the Beijing-Tianjin-Hebei region.

Methodology and data sources

Study area

The Beijing-Tianjin-Hebei region located in the northern part of the North China Plain, including Beijing Municipality, Tianjin Municipality, and Hebei Province, with a length of 735 km from north to south and a width of 576 km from east to west, and a variety of landforms, including plains, mountains, and plateaus. The terrain of Beijing-Tianjin-Hebei is tilted in a step-like manner from northwest to southeast, showing a high distribution in the northwest and a low distribution in the southeast (Fig. 1 Schematic of the study area). According to statistics, the gross regional product in 2020 was 86,393.20 billion yuan, the resident population was 110,369,000 people, and the urbanization level was 68.60%. However, the current Beijing-Tianjin-Hebei region still has problems such as irrational land use and high pressure on carbon emissions, which limit the high-quality development of the region.

Estimation of carbon emissions

Direct carbon accounting

Cropland and construction land were taken as carbon sources, and forest land, grassland, watersheds and unused land were taken as carbon sinks. The carbon emissions from cropland, forest land, grassland, watersheds and unused land were measured using the direct carbon emission factor method, with the formula:

$$C = \sum e_i = \sum S_i \delta_i, \quad (1)$$

where c denotes the amount of carbon emission (absorption) of cropland, forest land, grassland, watershed and unused land; S_i denotes the area of land type i , δ_i denotes the carbon emission coefficient of land type i , where a positive value indicates carbon emission and a negative value indicates carbon sequestration. In this study, the carbon emission coefficients of different land use types were determined with reference to the results of existing research^{34,35} (Table 1.).

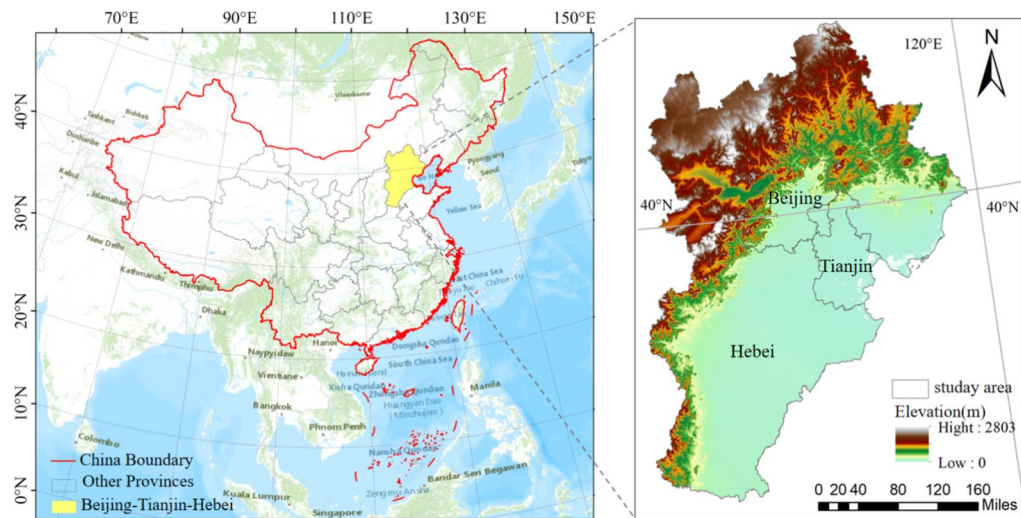


Figure 1. Schematic of the study area. Maps created in ArcMap 10.7 software.

Land type	Carbon emission coefficient
Cropland	0.0422
Forestland	-0.0578
Grassland	-0.0021
Water body	-0.0252
Unused land	-0.0005

Table 1. Carbon emission coefficient for land use ($\text{kg}\cdot\text{m}^{-2}\cdot\text{a}^{-1}$, positive values are carbon sources, while negative values are carbon sinks.).

Indirect carbon emissions

Carbon emissions from construction land are generally measured indirectly through the carbon emission coefficients of various energy consumptions during their utilization, and their standard coal conversion factors and carbon emission coefficients are shown in Table 2 with the following formulae:

$$\sum ec_i = \sum_{i=1}^9 m_i \theta_i \mu_i, \quad (2)$$

where, ec_i denotes all types of carbon emissions from energy consumption, unit million tons; m_i denotes the consumption of energy i ; θ_i denotes the standard coal conversion parameter of energy i ; μ_i denotes the carbon emission factor of energy i .

Type	Standard coal conversion factor	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	1.4571	0.5921
Fuel oil	1.4286	0.6185
Natural gas	13.301	0.4483
Electricity	1.229	0.7476

Table 2. Energy carbon emission factor values.

GTWR regression model

The GTWR considers the non-stationarity of space-time and introduces the time dimension into the geographically weighted regression model. This effectively overcomes the limitation of the traditional geographically weighted regression model (GWR), which only considers spatial influence. The GTWR fully reflects the temporal change of variable data and reveals heterogeneity of the variables in both time and space. This better explains the spatio-temporal relationship between the variables and the dependent variable. This paper employs the GTWR model to investigate the spatial and temporal factors that affect carbon emissions in Beijing-Tianjin-Hebei, using the following formula³⁶:

$$y_i = \beta_0(\mu_i, \nu_i, t_i) + \sum_k \beta_k(\mu_i, \nu_i, t_i)X_{ik} + \varepsilon_i, \quad (3)$$

where, y_i represents the dependent variable; β_0 represents the intercept; μ_i , ν_i and t_i represent the latitude, longitude and time of the i th point; β_k represents the fit coefficient of the k th variable at the i th point; X_{ik} represents the value of the k th independent variable at the i th point; ε_i represents the random error.

Indicator system

Based on the existing research literature and statistical^{37,38}, the indicator system comprises of five aspects: total population, economic development, industrial structure, land use degree, and landscape patterns, the following five indicators have been selected to construct the system:

- (1) Total Population (TP), expressed as the resident population at the end of the year, in tens of thousands.
- (2) Economic Level (EL), represented by total GDP, representing the economic development of the region, measured in ten thousand yuan.
- (3) Industrial Structure (IS), the proportion of added value of the tertiary industry in GDP, indicating the structure of the economy, measured in percentage.
- (4) Degree of Land Use (DT), land area of built-up areas, reflecting the extent of land utilization, measured in square kilometers.
- (5) Landscape Patterns (LP), represented by Interspersion and juxtaposition index (IJI), a measure of the spatial arrangement of land covers, measured in percentage.

These five indicators have been used to construct the indicator system for the influencing factors of carbon emissions (refer to Table 3.).

where TP, EL, IS and DT are obtained directly from the Statistical Yearbook, LP are indicators extracted from our secondary processing of land use data using FRAGSTATS 4.2.IJI, Landscape fragmentation index, Index range is (0, 100). Smaller values indicate that patches are less adjacent to patches of the same type and less adjacent to patches of a different type, the specific formula for its calculation is as follows.

$$IJI = \frac{-\sum_{i=1}^m \sum_{k=i+1}^m [\frac{e_{ik}}{E} \ln \frac{e_{ik}}{E}]}{\ln(m-1)} \times 100\%, \quad (4)$$

where: e_{ik} denotes the neighbouring edge length of each patch type adjacent to a patch type i ; E denotes the total edge length of patch i ; m denotes the total number of patch types in the landscape.

Data

The current land use data from 2000 to 2020 in this paper come from the China Land Cover Dataset (CLCD) based on the Google Earth Engine (GEE) platform released by the team of professors Yang Jie and Huang Xin from Wuhan University³⁹. The spatial resolution of the data is 30 m. The land use types in the study area are classified as cropland, forest land, grassland, water, construction land, and unused land. This classification is based on relevant studies by scholars⁴⁰, as well as the natural environment, socio-economic characteristics, and actual land use changes in the area. The socio-economic data adopted in this paper is primarily sourced from the 2000–2020 China Urban Statistical Yearbook, Beijing Statistical Yearbook, Tianjin Statistical Yearbook, and Hebei Statistical Yearbook.

Indicators	Interpretation	Unit
TP	Total population (Year-end resident population)	Ten thousand people
EL	Economic level (Total GDP)	Ten thousand yuan
IS	Industrial structure (Value added of tertiary sector as a share of GDP)	%
DT	Degree of land use (Land area of built-up areas)	km ²
LP	Landscape patterns (Interspersion and juxtaposition index, IJI)	%

Table 3. Research indicators and interpretation.

Results

Analysis of the historical land use situation

Using the spatial analysis, reclassification, and statistical analysis tools in ArcGIS 10.7 software, we obtained five land-use spatial pattern maps for the Beijing-Tianjin-Hebei region in 2000, 2005, 2010, 2015, and 2020, respectively. Figure 2 reflects that the land use types in the study area are mainly dominated by farmland, forests, and grasslands. Among them, farmland is mainly distributed in the central and southeastern regions of Beijing-Tianjin-Hebei, with large areas of forests and grasslands concentrated in the mountainous and hilly areas of the west and northeast, particularly prominent in Zhangjiakou and Chengde cities. The spatial distribution of construction land is highly consistent with farmland, presenting a scattered distribution in the central and southeastern regions. Water areas are mainly distributed in Baoding City in the central region and coastal cities such as Tianjin, Tangshan, Qinhuangdao, and Cangzhou in the east. Unused land, due to its low proportion, is not prominent in spatial distribution and is scattered in Zhangjiakou and Chengde cities.

Changes in spatial and temporal patterns of land use

As shown in Fig. 3, the land use pattern in the Beijing-Tianjin-Hebei region changed significantly from 2000 to 2020. Cropland decreases, construction land increases, forest and grassland areas are expanded, and watersheds and unused land change to a lesser extent. A total of 29,100.3138km² of land is converted, of which cropland has the greatest change, mainly to construction land, grassland and forest land. Grassland was mostly converted to cropland and forest land, and a small amount was converted to construction land. The change in water area is small, and the increase in construction land is significant, mainly from the transfer of cropland.

Characteristics of spatial and temporal evolution of carbon emissions from land use Analyses of carbon emissions from different land-use types

As shown in Table 4 and Fig. 4 from 2000 to 2020, the total carbon emissions from land use in Beijing-Tianjin-Hebei continued to grow from 140.1143 to 347.3489 million tons, with a net increase of 207.2347 million tons. The construction land is the main source of carbon, with a net increase of 208.0583 million tons; and carbon emissions from cropland decreased slightly. Forest land is the main carbon sink, with a small increase in carbon sink; the carbon absorption capacity of watershed decreased slightly and was stable overall. The carbon absorption capacity of grassland and unused land remained basically unchanged, contributing less to the carbon sink.

Evolution of spatial patterns of carbon emissions from land use

This paper classifies the land use carbon emissions of prefecture-level cities into different levels. The zones are categorized based on carbon emissions: micro-emission zone (less than 5 million tons), light emission zone (5 million tons–10 million tons), general emission zone (10 million tons–15 million tons), medium emission zone (15 million tons–20 million tons), heavy carbon emission zone (20 million tons–25 million tons), and extremely heavy carbon emission zone (25 million tons or more).

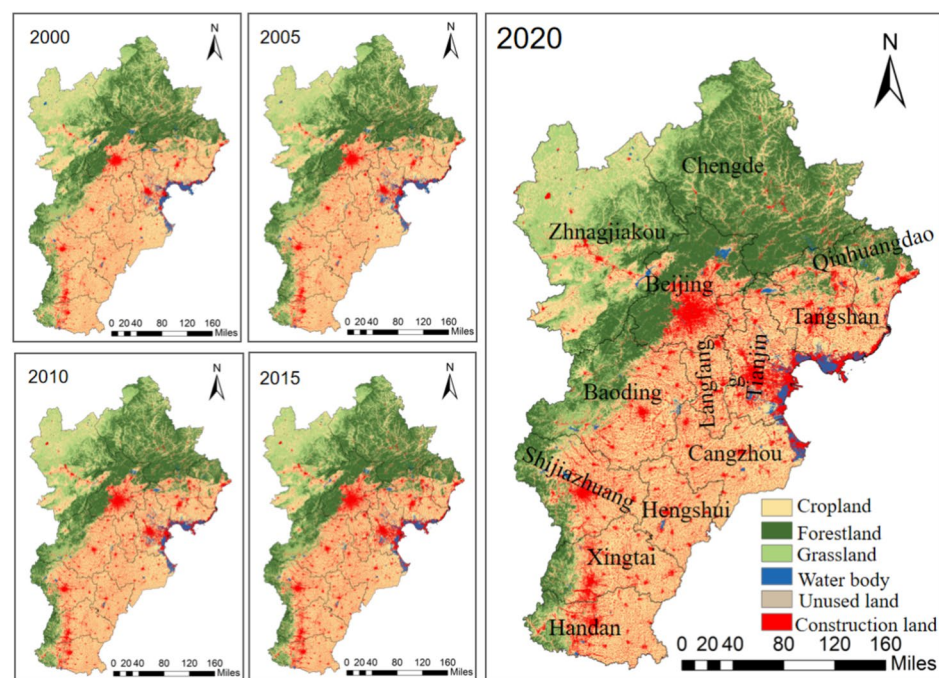


Figure 2. Spatial pattern of land use in the Beijing-Tianjin-Hebei region. Maps created in ArcMap 10.7 software.

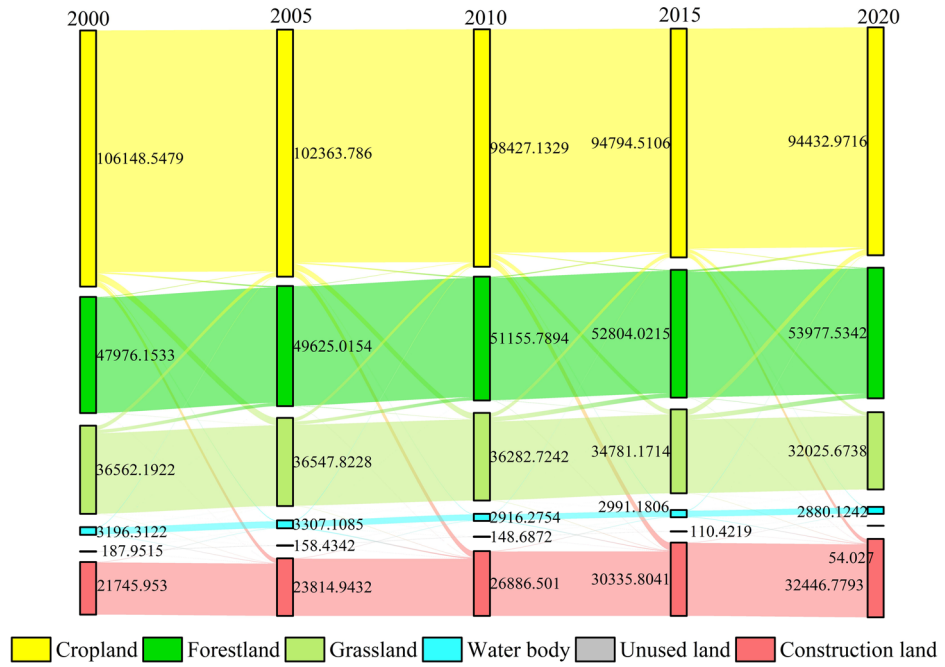


Figure 3. Beijing-Tianjin-Hebei land use area change transfer Sankey diagram.

Year	Carbon source unit 10 ⁴ t		Carbon absorption unit 10 ⁴ t			
	Construction land	Cropland	Forestland	Grassland	Water body	Unused land
2000	13856.5241	447.9469	-277.3022	-7.6781	-8.0547	-0.0094
2005	23296.2217	431.9752	-286.8326	-7.6750	-8.3339	-0.0079
2010	32163.3514	415.3625	-295.6805	-7.6194	-7.3490	-0.0074
2015	33784.8728	400.0328	-305.2072	-7.3040	-7.5378	-0.0055
2020	34662.3585	398.5071	-311.9901	-6.7254	-7.2579	-0.0027

Table 4. Carbon Emission from Land Use in Beijing-Tianjin-Hebei.

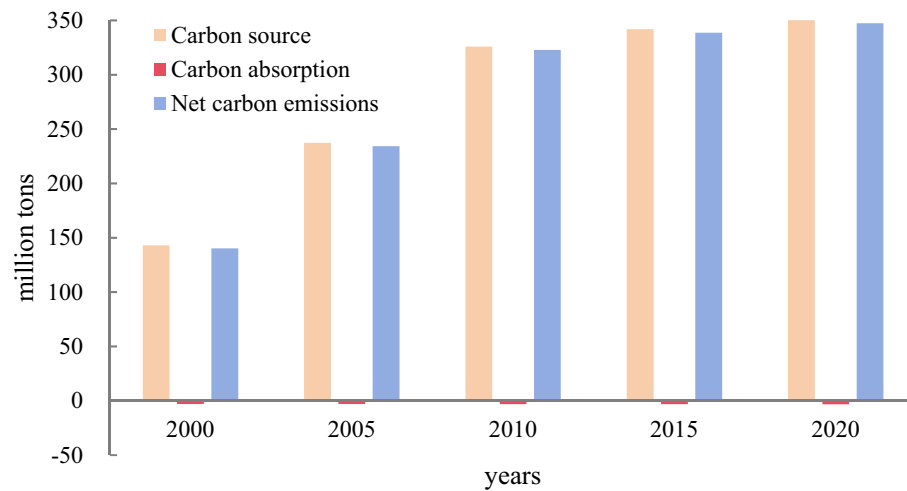


Figure 4. Trend of annual carbon emissions in Beijing-Tianjin-Hebei.

Spatial differences in carbon emissions from land use at the municipal scale of Beijing-Tianjin-Hebei are evident. Between 2000 and 2020, the spatial pattern of carbon emissions changed significantly, with an increase in the number of general and above carbon emission zones. The main changes occurred in the western and southwestern parts of the country. In 2020, there was a significant reduction in carbon emissions compared to 2010, with a decrease in the number of areas with very high carbon emissions. The differences in carbon emissions are closely linked to the type of industry, level of industrialization, and economic development, with traditional industrial cities having high carbon emissions, for example, Beijing, Tianjin, and Tangshan. Some cities with a high GDP per capita have high carbon emissions. However, Qinhuangdao has relatively low carbon emissions due to its well-developed tourism industry. Additionally, the expansion of urban land use also contributes to the growth of carbon emissions (Fig. 5).

The center of gravity of carbon emissions in Beijing-Tianjin-Hebei is located in Langfang (see to Fig. 6). The trend indicates that carbon emissions in Tianjin and Tangshan initially decrease before increasing again. Changes in the ellipse area demonstrate a gradual aggregation of carbon emissions towards the northeast-southwest direction, with a slightly stronger aggregation trend in the east-west direction than in the north-south direction. The spatial agglomeration of carbon emissions in Beijing-Tianjin-Hebei has shown a decreasing trend, despite fluctuations. (see to Table 5.).

Contributing factors

GTWR estimation results

The prerequisite for estimation using the GTWR model is to ensure that there is no multicollinearity between the explanatory variables. In this paper, the model was analyzed for multicollinearity using Spss25, and the results showed that the variance inflation factor (VIF) of all the explanatory variables was less than 10, indicating that there was no multicollinearity among the explanatory variables as shown in Table 6.

The correlation analysis of each driver with carbon emissions is shown in Table 6., TP, EL, IS, UE and LP are positively correlated with carbon emissions, and correlation coefficients all reached the 0.01 significant level, among which the correlation coefficients of TP and DT are the highest, 0.71 and 0.72 respectively, which indicates that the larger the total population and the larger the built-up area of the city, the larger the carbon emissions will be. The correlation between IS and LP is relatively low, at approximately 0.39 and 0.37, respectively. In terms of the landscape patterns agglomeration index, IJI is significantly positively correlated with carbon emissions, indicating that the lower the degree of neighbourhood or fragmentation of patches and the lower the degree of patch agglomeration, the lower the carbon emissions.

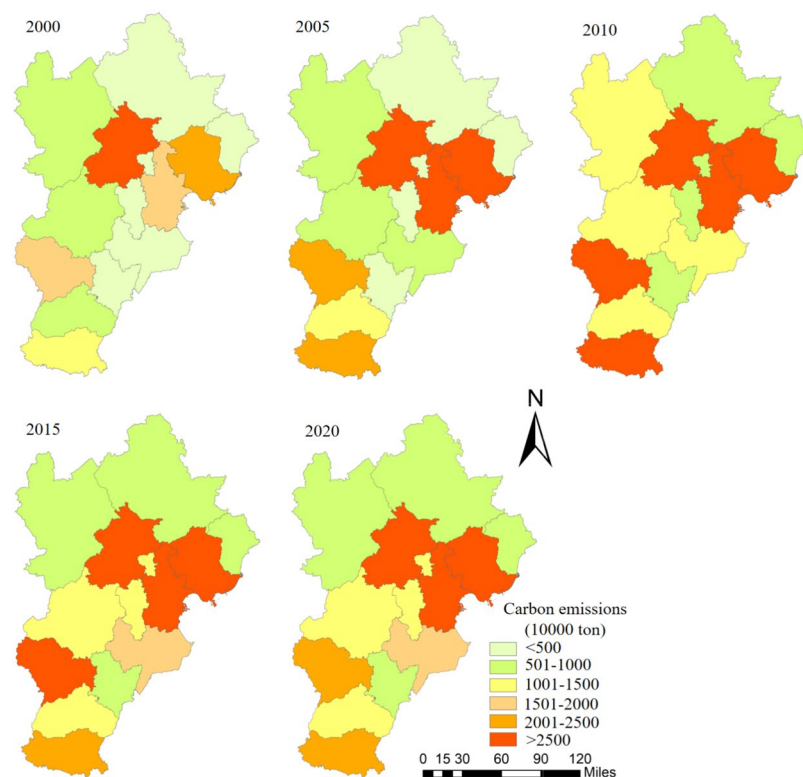


Figure 5. Spatial and temporal distribution of carbon emissions from land use in Beijing-Tianjin-Hebei. Maps created in ArcMap 10.7 software.

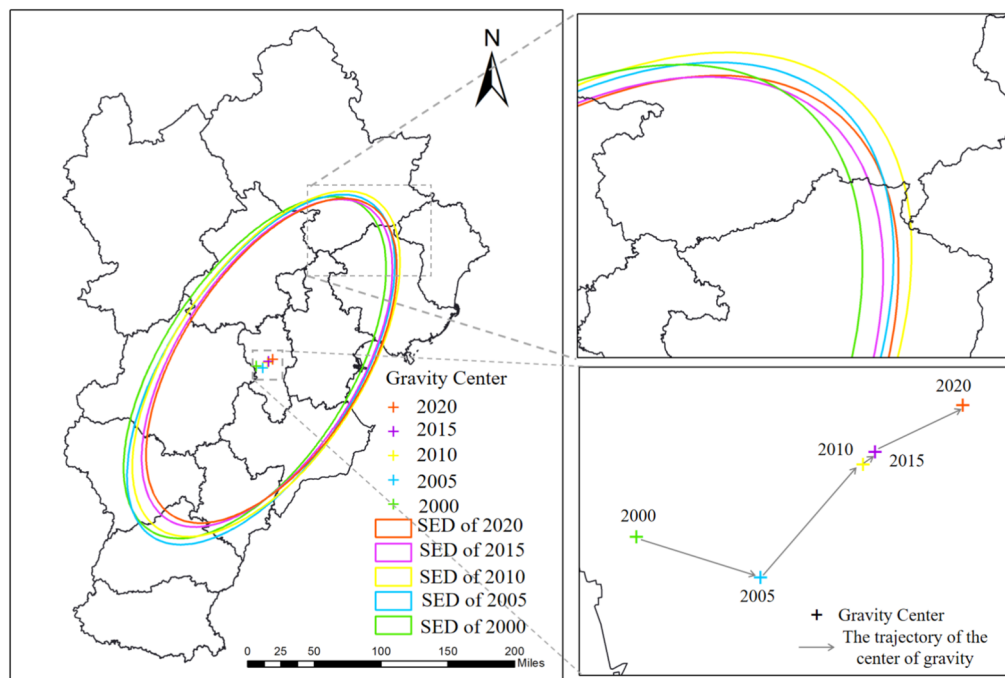


Figure 6. The distribution of standard deviational ellipse and gravity center shift trajectory. Maps created in ArcMap 10.7 software.

Year	Center X/°	Center Y/°	Long half-axis/km	Short half-axis/km	Flattening rate	Displacement/km
2000	116.33	39.09	299.47	146.04	0.51	
2005	116.42	39.06	308.17	145.27	0.53	10.32
2010	116.50	39.11	304.49	147.21	0.52	11.94
2015	116.51	39.12	286.49	140.54	0.51	1.36
2020	116.58	39.14	284.40	141.08	0.50	7.86

Table 5. The parameters of carbon emission standard deviational ellipse and gravity center in the study area.

Indicators	Correlation coefficient	VIF	Tolerance
Total population(TP)	0.71*	4.08	0.26
Economic level(EL)	0.68*	5.29	0.19
Industrial structure(IS)	0.39*	2.30	0.44
Degree of land use(DT)	0.72*	7.30	0.14
Landscape patterns(LP)	0.37*	1.17	0.85

Table 6. Multicollinearity and significance diagnosis results. (* $p \leq 0.01$).

Analysis of the temporal heterogeneity of regression coefficients for factors influencing carbon emissions

The carbon emission driver model of Beijing-Tianjin-Hebei prefecture-level cities was established and tested using ArcGIS software. The results indicate that the GTWR model has an AICc value of -404.289 and an adjusted coefficient of determination R^2 of 0.95 , demonstrating a well-fitted regression equation. The spatial distribution maps of the regression coefficients for the factors influencing carbon emissions in the prefecture-level cities of Beijing-Tianjin-Hebei were generated separately for each year to investigate their temporal heterogeneity.

(1) Analysis of the impact of total population on carbon emissions over time.

Figure 7 shows the spatial distribution of the regression coefficients of the total population of Beijing-Tianjin-Hebei land-use carbon emissions from 2000 to 2020. The data indicates a decreasing trend in the influence of total population on land-use carbon emissions. During the period of 2000–2020, areas with high coefficients were mainly located in Chengde, Qinhuangdao, Handan, and Xingtai. These areas are characterized by a large

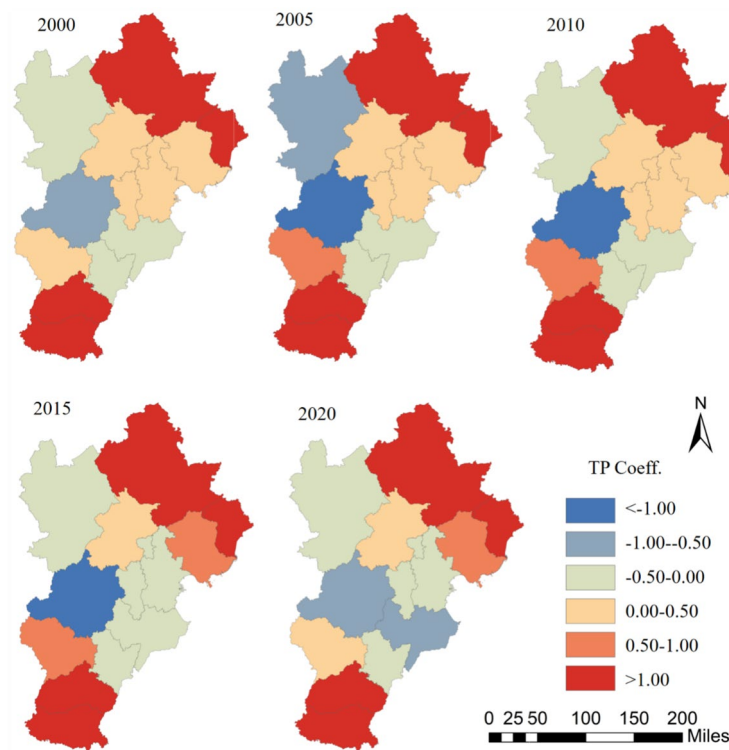


Figure 7. Spatial distribution of regression coefficients of total population in prefecture-level cities. Maps created in ArcMap 10.7 software.

population base, fast growth rate, high urbanization level, and rapid economic development. Conversely, low-value areas are concentrated in Baoding, Cangzhou, and Hengshui, showing a negative correlation. The data indicate that there is a positive correlation between the total population and carbon emissions in the Beijing-Tianjin-Hebei region. The increase in total population no longer has a singular positive effect on carbon emissions, as it has been observed in previous studies³³. This is due to the transformation and upgrading of industries in the Beijing-Tianjin-Hebei region, technological advances, a greater agglomeration of population and economic activities, and a greater focus on low-carbon living. However, the growth of total population still leads to more energy consumption to meet the demands of rising living standards.

(2) Temporal heterogeneity analysis of the impact of economic development on carbon emissions.

During the study period, it was observed that the relationship between GDP and carbon emissions from land use in the Beijing-Tianjin-Hebei region followed an increasing and then decreasing trend. Specifically, the economic development of Beijing facilitated the optimization of both the economic and energy structures, resulting in a negative correlation with carbon emissions. Scholars have demonstrated an inverted U-shaped relationship between economic growth and carbon emissions. This means that as the economy develops, the impact of economic growth on carbon emissions initially increases and then decreases. At the start of the study, the economy of Beijing-Tianjin-Hebei was relatively underdeveloped and had a minor impact on carbon emissions. However, over the past two decades, the economy of the region has developed rapidly and has become a significant contributor to carbon emissions. The impact coefficients in 2015 and 2020 are slightly lower than those in 2010, suggesting that the impact of economic development in Beijing-Tianjin-Hebei on carbon emissions in 2020 is on the downward slope of the inverted ‘U’ curve. It is expected that the degree of influence will gradually decrease with continued economic development (Fig. 8).

(3) Temporal heterogeneity analysis of the impact of industrial structure on carbon emissions.

Industrial structure is characterized by the proportion of the added value of the tertiary industry to the regional GDP. During the study period, the impact of the proportion of the tertiary industry in Beijing-Tianjin-Hebei on carbon emissions is negative, and only Beijing has a positive correlation with carbon emissions in most years, with a stable degree of influence, which implies that the increase in the proportion of the tertiary industry in high-emission industries in Beijing has led to an increase in the level of carbon emissions. In other cities, the relationship between industrial structure and carbon emissions is mainly negative, with Chengde, Qinhuangdao and Tangshan having the greatest influence, probably due to the low-carbon characteristics of the tertiary industry itself, government policy support, as well as the optimization of the energy structure and the improvement of energy use efficiency. These factors work together to make the increase in the proportion of tertiary industry particularly effective in reducing carbon emissions (Fig. 9).

(4) Temporal heterogeneity analysis of the impact of land use degree on carbon emissions.

As the land area of built-up areas increases, so does the carbon source, while the expansion of urban construction land leads to a decrease in carbon sink. The land area of built-up areas shows an obvious positive

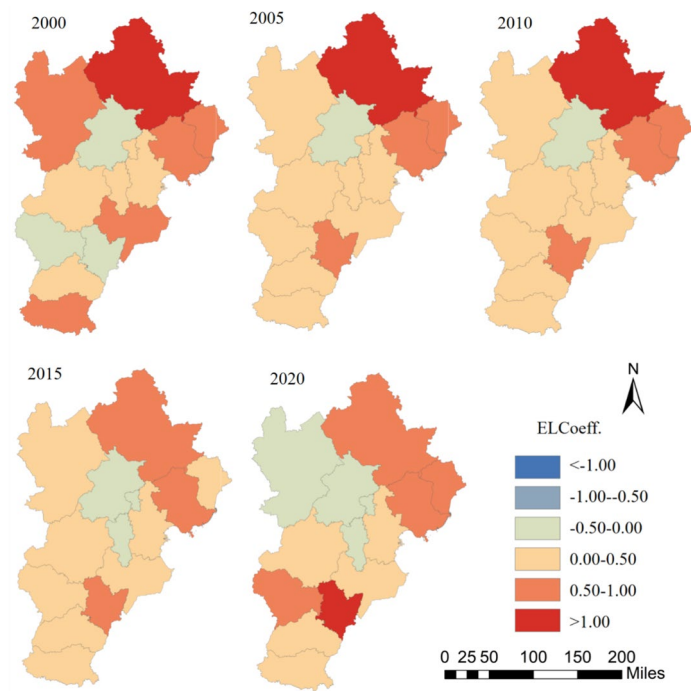


Figure 8. Spatial distribution of regression coefficients of economic development of prefecture-level cities. Maps created in ArcMap 10.7 software.

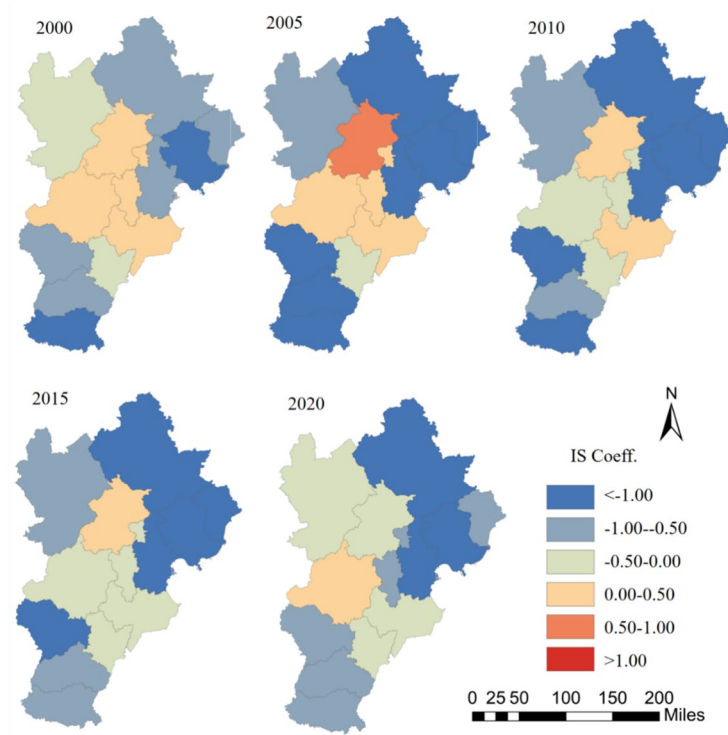


Figure 9. Spatial distribution of regression coefficients of industrial structure in Beijing-Tianjin-Hebei prefecture-level cities. Maps created in ArcMap 10.7 software.

correlation with carbon emissions in Beijing-Tianjin-Hebei, and the degree of influence is geographically heterogeneous. Overall (Fig. 10), the degree of influence of built-up land area on carbon emissions in Beijing-Tianjin-Hebei can be divided into 2 types. The land area of built-up area has a negative correlation with Chengde's carbon emissions, and the other areas have a positive correlation on the whole. Chengde City has rich natural resources and ecological advantages, so it is more inclined to protect the ecological environment in urban planning and land use, and limit the land use methods with high carbon emissions, such as industrial land and large-scale commercial development, and it will pay more attention to increasing the proportion of green land rate and ecological land use, and promote low-carbon, environmentally friendly land use patterns.

(5) Analysis of the impact of landscape patterns on carbon emissions.

The relationship between landscape patterns and carbon emissions varies across different cities. The study found that Landscape patterns aspects are generally positively correlated with carbon emissions. Specifically, low levels of patch proximity and agglomeration are associated with low carbon emissions. In Qinhuangdao, Tianjin, Chengde, and Zhangjiakou, landscape patterns is positively associated with carbon emissions, while in Handan, Xingtai, and Shijiazhuang, it is negatively associated. Handan and other cities are focusing on land intensification and ecology to reduce carbon emissions. Qinhuangdao and Tianjin, being coastal cities, have experienced faster economic development, but this has also led to higher carbon emissions. These cities have prioritised economic development and industrial expansion during the urbanization process. As a result, the land use types are dominated by industrial and transport land, which typically produce higher carbon emissions. Despite Chengde and Zhangjiakou serving as ecological barriers, they are still under pressure to emit carbon (Fig. 11).

Discussion

Dynamic relationship between land use and carbon emissions

From 2000 to 2020, the area of construction land in Beijing-Tianjin-Hebei increases significantly, with an increase of 11,044.5777 km². Construction land is a fundamental spatial carrier for human habitation, recreation, and industrial production. It is also a significant source of carbon emissions from energy, industrial processes, product use, and residential life. Its carbon emission intensity is much higher than that of other land-use types⁴¹. The trend of carbon emissions from land use in the Beijing-Tianjin-Hebei region between 2000 and 2020 shows an initial increase followed by a period of stability. The period between 2000 and 2010 was characterized by accelerated regional land urbanization, which led to a rapid expansion of urban land use and population growth⁴². This, in turn, exacerbated energy consumption and resulted in a significant rise in carbon emissions across the region. However, since 2010, with the implementation of the Main Functional Area Plan and the strictest farmland protection policy, the intensity of urban land expansion in the Beijing-Tianjin-Hebei region has significantly decreased, and urban land growth has gradually shifted to orderly expansion. In addition, the

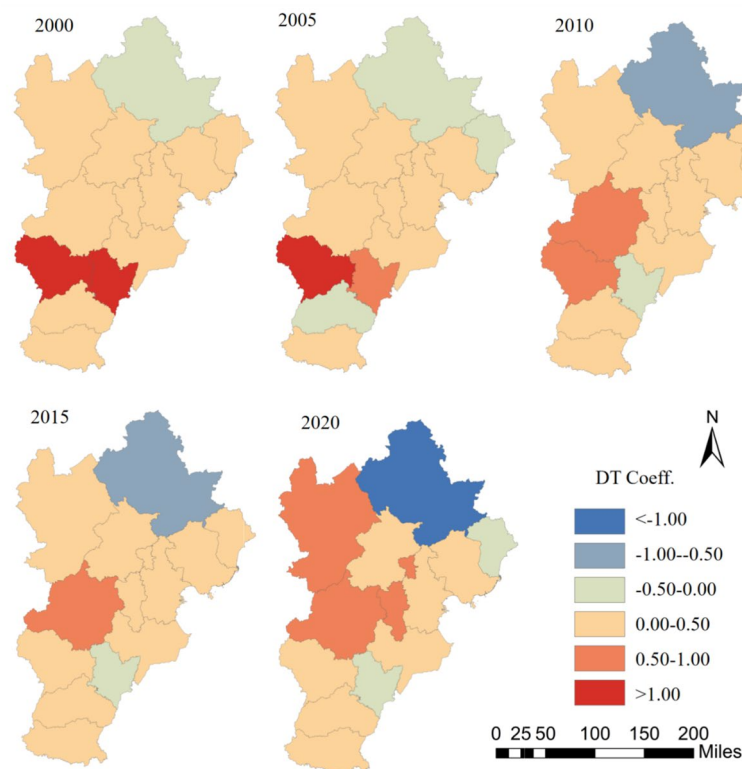


Figure 10. Spatial distribution of regression coefficients of land use degree in prefecture-level cities in Beijing, Tianjin and Hebei. Maps created in ArcMap 10.7 software.

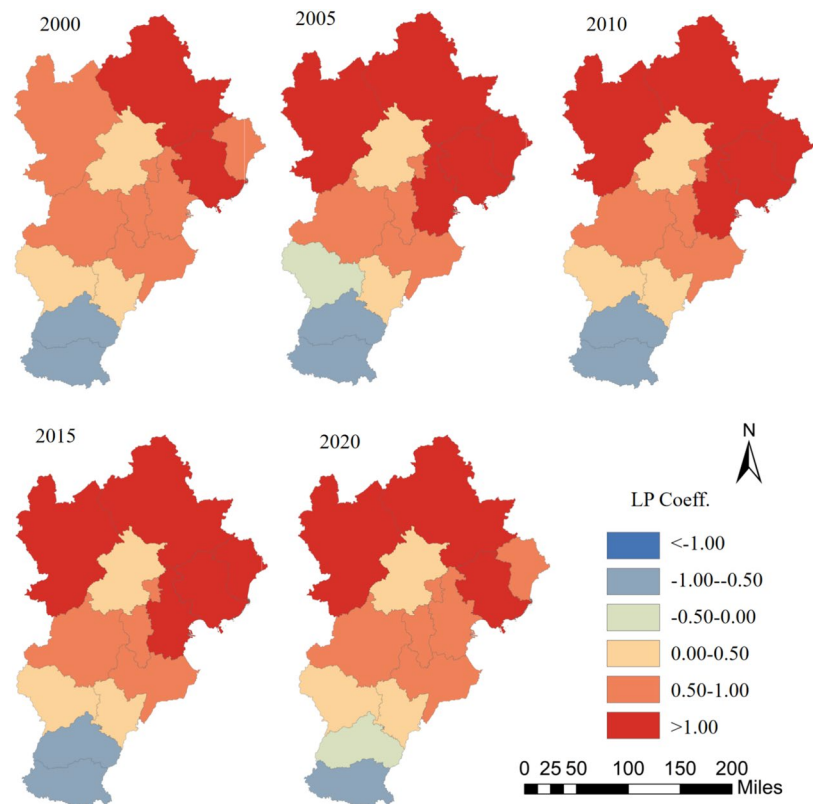


Figure 11. Spatial distribution of regression coefficients of landscape patterns of prefecture-level cities in Beijing-Tianjin-Hebei. Maps created in ArcMap 10.7 software.

Beijing-Tianjin-Hebei coordinated development strategy has promoted the relocation and upgrading of regional industries, resulting in lower energy consumption in economic development. As a result, the rapid growth of carbon emissions in the region has been effectively curbed⁴³.

Analysis of carbon emission attribution

Population growth drives energy consumption and carbon emissions. Although the economic level remains the primary cause of carbon emissions growth in Beijing-Tianjin-Hebei, its role is gradually diminishing due to economic restructuring and the implementation of the coordinated development strategy. In recent years, the Beijing-Tianjin-Hebei region has experienced rapid economic growth, which has been accompanied by a decline in energy consumption per unit of GDP. This has led to an increase in the decoupling of carbon emissions from economic growth⁴⁴. An increased share of the tertiary sector can help reduce carbon intensity⁴⁵. However, it is important to note that an increase in the proportion of high-emitting sectors could lead to an increase in total carbon emissions⁴⁶.

Chengde City exhibits a negative correlation between its built-up area and carbon emissions in the Beijing-Tianjin-Hebei region. This is mainly due to the city's emphasis on ecological protection and green development in land use. In comparison to other regions, Chengde City prioritises the sustainable use of land resources, which limits the growth of carbon emissions. Due to its small built-up area, Chengde should focus on intensive and efficient land use during the urbanization process to avoid increased carbon emissions from over-expansion⁴⁷. In the Beijing-Tianjin-Hebei region, rapid economic development and urbanization are likely to increase the proportion of land use types that have high carbon emissions, such as industrial and commercial land. Urbanization in these areas often leads to significant energy consumption and carbon emissions, particularly during the construction of factories and commercial facilities⁴⁸. Furthermore, the land use type in various regions has a significant impact on carbon emissions. Agricultural and forest lands are crucial for carbon storage and sequestration, whereas industrial and transportation lands are the primary sources of carbon emissions⁴⁹. Therefore, variations in land use types are also a significant factor that leads to different carbon emissions. The correlation between the landscape pattern index and carbon emissions of various cities in the Beijing-Tianjin-Hebei region is influenced by several factors, such as land use type, landscape pattern, economic development, urbanization process, and natural factors. In promoting the synergistic development of the Beijing-Tianjin-Hebei region, it is important to optimize the land use structure, improve the landscape pattern, reduce carbon emissions, and achieve sustainable development⁵⁰.

Through the previous analysis, we have identified the key role of land use change in carbon emissions in the Beijing-Tianjin-Hebei region, especially in urbanization and the transformation of agricultural activities.

However, this analysis only focuses on the direct effects of land use and ignores other potentially important influencing factors, and in order to more fully understand the drivers of carbon emissions, we need to expand the perspective to the socio-economic level. Two factors in particular, policy change and technological progress, whose impact on carbon emissions cannot be ignored.

The Beijing-Tianjin-Hebei region has significantly reduced carbon emissions in recent years by implementing strict energy policies, such as promoting clean energy alternatives and limiting coal use. For example, by promoting the use of renewable energy such as photovoltaic and wind power, the consumption of fossil energy is effectively reduced. Guan³¹ points out that the changes in energy carbon emissions in the Beijing-Tianjin-Hebei region fully demonstrate the significant impact of policies on carbon emissions. By formulating and implementing effective carbon emission reduction policies, optimizing energy structure and promoting clean energy utilization, carbon emission growth can be effectively controlled and green sustainable development of regional economy can be promoted. According to the research of Zhong et al.⁵¹, since the regional coordinated development policy in Beijing-Tianjin-Hebei region was proposed in 2014, it has significantly reduced carbon emissions through structural and technological effects, especially by optimizing the energy structure, and effectively reversed the long-term growth trend of carbon emissions. Technological progress provides an important means for reducing carbon emissions, which can reduce energy consumption and carbon emissions through energy conservation, industrial upgrading and other effects. Kim⁵² selected the data of 23 cities in South Korea from 1989 to 2013, and analyzed the contribution of each city's scientific and technological progress to reducing carbon emissions based on the spatial state model. Yang et al.⁵³ believe that scientific and technological progress does not always promote carbon emission reduction, but also leads to more energy consumption through promoting economic growth, which ultimately increases carbon emissions. Ying Fan et al.⁵⁴ selected the data of a number of countries from 1975 to 2000, classified them according to the income level of different countries, and conducted a research using the STIRPAT Model. The results showed that countries with different levels of economic development have different degrees of impact on carbon emissions from technological progress. In summary, policy changes and technological progress are important socio-economic factors affecting carbon emissions in the Beijing-Tianjin-Hebei region. Future research is needed to explore the interaction of these factors with land use change in more depth to gain a fuller understanding of the drivers of carbon emissions. This will help us formulate more scientific and effective carbon emission reduction policies and promote the sustainable development of the Beijing-Tianjin-Hebei region.

Recommendations

(1) Precise Planning and Regional Coordination.

Based on the changes in the center of gravity of carbon emissions in Beijing-Tianjin-Hebei, make full use of the framework of the Beijing-Tianjin-Hebei Cooperative Development Strategy to strengthen cooperation and coordination among cities, and jointly promote low-carbon land use and low-carbon economic development, especially in areas with high carbon emissions, such as Beijing, Tianjin and Tangshan, to formulate a more precise policy on land use and industrial development. Optimize the land use structure, reduce land for high-carbon emission industries, and increase greenfield and ecological land.

(2) Strengthen ecological protection and restoration.

Increase the protection and restoration of ecosystem carbon sink functions, especially in key areas in the northeast-southwest direction, and strengthen the protection and construction of forests, wetlands and other ecosystems. Carry out restoration projects for degraded ecosystems to improve the stability and carbon storage capacity of ecosystems. For example, Chengde City can continue to strengthen ecological protection and green development, while other cities can improve the carbon sink capacity of their land by increasing the area of green space and building ecological corridors.

(3) Promoting industrial transformation and upgrading is the key to reducing carbon emissions. Led by the Beijing-Tianjin-Hebei coordinated development strategy, the transformation and upgrading of high-energy-consuming and high-emission industries should be actively promoted, and low-carbon and environmentally friendly emerging industries should be vigorously developed. At the same time, the development of the tertiary industry should be encouraged, especially low-carbon emission service industries such as information technology, finance and education. For high-emission industries within the tertiary sector, such as transport, catering and accommodation, they should be promoted for green and low-carbon transformation.

Shortcomings and prospects

Using the GTWR model, this study analyses the spatial and temporal heterogeneous characteristics of carbon emissions in Beijing-Tianjin-Hebei and explores the influencing factors. However, it only considers carbon emissions from energy consumption and does not cover the comprehensive carbon emissions of the entire society. Furthermore, the study does not include the simulation and prediction of future carbon emissions. As a next step, it is important to comprehensively consider carbon emission scenarios and simulate carbon emissions under different development scenarios. This will provide valuable policy recommendations for achieving carbon neutrality and carbon peaking.

Conclusion

(1) The carbon emissions of Beijing-Tianjin-Hebei have continued to grow, albeit at a slower rate, from 140.1143 million tons in 2000 to 347.3489 million tons in 2020. The growth was rapid before 2010, after which it levelled off. The expansion of construction land is the primary cause of the increase in carbon emissions, and it also affects the distribution of carbon emission centers.

(2) The carbon emissions in Beijing-Tianjin-Hebei exhibit significant spatial and temporal heterogeneity. The amount of carbon emissions is distributed randomly, but core cities such as Beijing and Tianjin consistently emit high levels of carbon. During the study period, carbon emissions in the Beijing-Tianjin-Hebei region showed a small fluctuation, with a trend of initially increasing and then decreasing, ultimately showing an overall decrease.

(3) The spatial and temporal heterogeneity of the factors influencing carbon emissions in Beijing-Tianjin-Hebei is evident. Factors such as total population, economic development, industrial structure, degree of land use, and landscape patterns have a significant impact on carbon emissions. An increase in total population, economic development, and expansion of construction land use results in a rise in carbon emissions. Carbon emissions from land use exhibit significant spatial heterogeneity across regions due to variations in population, land use, industrial structure, landscape patterns, and economy.

Data availability

Data availability The datasets generated during and/or analysed during the current study are available from the corresponding author on reasonable request.

Received: 22 April 2024; Accepted: 6 August 2024

Published online: 16 August 2024

References

1. Wang, S. J., Xie, Z. H. & Wang, Z. H. Spatial and temporal evolution of carbon emissions in China's counties and the factors affecting them. *Acta Geogr. Sin.* **76**(12), 3103–3118 (2021).
2. Wang, S. *et al.* Multi objective programming model of low-cost path for China's peaking carbon dioxide emissions and carbon neutrality. *Res. Environ. Sci.* **34**(9), 2044–2055 (2021).
3. Yang, F., He, F., Li, S., Li, M. & Wu, P. A new estimation of carbon emissions from land use and land cover change in China over the past 300 years. *Sci. Total Environ.* **863**, 160963 (2023).
4. Watson, Robert Tony *et al.* *Land Use, Land-Use Change, and Forestry: A Special Report of the Intergovernmental Panel on Climate Change*. <https://www.ipcc.ch/report/land-use-land-use-change-and-forestry> (2000).
5. Rong, T. *et al.* Spatial correlation evolution and prediction scenario of land use carbon emissions in China. *Ecol. Inform.* **71**, 101802 (2022).
6. Liu, Q., Wu, S., Lei, Y., Li, S. & Li, L. Exploring spatial characteristics of city-level CO₂ emissions in China and their influencing factors from global and local perspectives. *Sci. Total Environ.* **754**, 142206 (2021).
7. Xu, J. Study on spatiotemporal distribution characteristics and driving factors of carbon emission in Anhui Province. *Sci. Rep.* **13**, 14400 (2023).
8. He, J. & Yang, J. Spatial-temporal characteristics and influencing factors of land-use carbon emissions: An empirical analysis based on the GTWR model. *Land* **12**, 1506 (2023).
9. Fang, W., Luo, P., Luo, L., Zha, X. & Nover, D. Spatiotemporal characteristics and influencing factors of carbon emissions from land-use change in Shaanxi Province, China. *Environ. Sci. Pollut. Res.* **30**, 123480–123496 (2023).
10. Xu, Y. *et al.* Study on the spatio-temporal evolution characteristics and driving mechanism of China's carbon emissions. *Humanit. Soc. Sci. Commun.* **10**, 1–11 (2023).
11. Wen, Z., Yang, Z. & Xing, Q. A comprehensive evaluation of regional carbon emission based on the composite model in China: A case study of Huaibei city (China). *Sci. Rep.* **13**, 15387 (2023).
12. Jiang, P. *et al.* Research on spatial and temporal differences of carbon emissions and influencing factors in eight economic regions of China based on LMDI model. *Sci. Rep.* **13**, 7965 (2023).
13. Cheng, Y., Tang, Y., Zhou, B. & Feng, H. Spatiotemporal analysis of national carbon emission and regional carbon simulation in China. *Environ. Sci. Pollut. Res.* **31**, 10702–10716 (2024).
14. Luo, X., Ao, X., Zhang, Z., Wan, Q. & Liu, X. Spatiotemporal variations of cultivated land use efficiency in the Yangtze River Economic Belt based on carbon emission constraints. *J. Geogr. Sci.* **30**, 535–552 (2020).
15. Yang, X. & Liu, X. Carbon conduction effect and temporal-spatial difference caused by land type transfer in Chang-Zhu-Tan Urban Agglomeration from 1995 to 2018. *Acta Ecol. Sin.* **42**, 338–347 (2022).
16. Duan, C., Zhu, W., Wang, S. & Chen, B. Drivers of global carbon emissions 1990–2014. *J. Clean. Prod.* **371**, 133371 (2022).
17. Cui, E., Ren, L. & Sun, H. Analysis of energy-related CO₂ emissions and driving factors in five major energy consumption sectors in China. *Environ. Sci. Pollut. Res.* **23**, 19667–19674 (2016).
18. Luo, F. *et al.* Carbon emissions and driving forces of China's power sector: Input-output model based on the disaggregated power sector. *J. Clean. Prod.* **268**, 121925 (2020).
19. Wang, P. *et al.* CCUS development in China and forecast its contribution to emission reduction. *Sci. Rep.* **13**, 17811 (2023).
20. Zhengnan, L., Yang, Y. & Jian, W. Factor decomposition of carbon productivity Chang in China's main industries: Based on the Laspyres decomposition method. *Energy Procedia* **61**, 1893–1896 (2014).
21. Huo, T. *et al.* Exploring the impact of urbanization on urban building carbon emissions in China: Evidence from a provincial panel data model. *Sustain. Cities Soc.* **56**, 102068 (2020).
22. Qin, H. *et al.* Carbon dioxide emission driving factors analysis and policy implications of Chinese cities: Combining geographically weighted regression with two-step cluster. *Sci. Total Environ.* **684**, 413–424 (2019).
23. Liu, J., Peng, K., Zuo, C. & Li, Q. Spatiotemporal variation of land-use carbon emissions and its implications for low carbon and ecological civilization strategies: Evidence from Xiamen-Zhangzhou-Quanzhou metropolitan circle, China. *Sustain. Cities Soc.* **86**, 104083 (2022).
24. Li, H., Li, Wei & Yao, X. L. Study on spatial and temporal variation of impacting factors of agricultural carbon emissions based on the GWR mode. *Sci. Technol. Manag. Res.* **39**(18), 238–245 (2019).
25. Hou, B., Yue, W. Z. & Wang, T. F. Spatiotemporal heterogeneity pattern and influencing factors of carbon emission metropolitan areas of China: A case of Shanghai. *Econ. Geogr.* **40**(9), 82–902 (2020).
26. Wang, Z., Peng, Y., Li, Y., Zhou, X. & Xie, Y. Exploration of influencing factors of land surface temperature in cities within the Beijing-Tianjin-Hebei Region based on local climate zone scheme. *IEEE J. Sel. Top. Appl. Earth Obs. Remote Sens.* **17**, 9728–9744 (2024).
27. Zhou, Y., Chen, M., Tang, Z. & Mei, Z. Urbanization, land use change, and carbon emissions: Quantitative assessments for city-level carbon emissions in Beijing-Tianjin-Hebei region. *Sustain. Cities Soc.* **66**, 102701 (2021).
28. Lou, T. *et al.* A heterogeneity study of carbon emissions driving factors in Beijing-Tianjin-Hebei Region, China, based on PGTWR model. *Int. J. Environ. Res. Public Health* **19**, 6644 (2022).
29. Chen, Li., Zhang, N., Wang, Y. & Hu, T. Driving factors and attribution analysis of carbon emission intensity change of Beijing-Tianjin-Hebei Region: Based on the perspective of subdivided industries and five-year plan, China. *Environ. Sci.* **2**, 22 (2023).

30. Yan, H., Guo, X., Zhao, S. & Yang, H. Variation of net carbon emissions from land use change in the Beijing-Tianjin-Hebei Region during 1990–2020. *Land* **11**, 997 (2022).
31. Guan, Q. Decomposing and decoupling the energy-related carbon emissions in the Beijing-Tianjin-Hebei Region using the extended LMDI and Tapio index model. *Sustainability* **15**, 9681 (2023).
32. Cai, Y. & Li, K. Spatiotemporal dynamic evolution and influencing factors of land use carbon emissions: Evidence from Jiangsu Province China. *Front. Environ. Sci.* **12**, 16 (2024).
33. Tang, Z., Wang, Y., Fu, M. & Xue, J. The role of land use landscape patterns in the carbon emission reduction: Empirical evidence from China. *Ecol. Indic.* **156**, 111176 (2023).
34. Liu, G. & Zhang, F. Land zoning management to achieve carbon neutrality: A case study of the Beijing-Tianjin-Hebei Urban Agglomeration, China. *Land* **11**, 551 (2022).
35. Wei, J., Xia, L., Chen, L., Zhang, Y. & Yang, Z. A network-based framework for characterizing urban carbon metabolism associated with land use changes: A case of Beijing city, China. *J. Clean. Prod.* **371**, 133695 (2022).
36. Ren, Y., Fang, C. & Li, G. Spatiotemporal characteristics and influential factors of eco-efficiency in Chinese prefecture-level cities: A spatial panel econometric analysis. *J. Clean. Prod.* **260**, 120787 (2020).
37. Zhang, Y., Zhang, Y., Zhang, Y., Gong, C. & Kong, Y. Analysis of the carbon emission driving factors and prediction of a carbon peak scenario—a case study of Xi'an city. *Heliyon* **8**, e11753 (2022).
38. Guo, W., Li, Y., Li, P., Zhao, X. & Zhang, J. Using a combination of nighttime light and MODIS data to estimate spatiotemporal patterns of CO₂ emissions at multiple scales². *Sci. Total Environ.* **848**, 157630 (2022).
39. Yang, J. & Huang, X. The 30 m annual land cover dataset and its dynamics in China from 1990 to 2019. *Earth Syst. Sci. Data* **13**, 3907–3925 (2021).
40. Liu, C., Hu, S., Wu, S., Song, J. & Li, H. County-level land use carbon emissions in China: Spatiotemporal patterns and impact factors. *Sustain. Cities Soc.* **105**, 105304 (2024).
41. Yu, R. & Tian, S. M. An analysis of land use and carbon emission in Hefei City based on carrying relationship. *J. Anhui Agric. Univ.* **43**(6), 939–945 (2016).
42. Liu, N. *et al.* Analysis of chlorophyll concentration in potato crop by coupling continuous wavelet transform and spectral variable optimization. *Remote Sens.* **12**, 2826 (2020).
43. Bai, X. *et al.* Hyperspectral estimation of apple canopy chlorophyll content using an ensemble learning approach. *Appl. Eng. Agric.* **37**, 505–511 (2021).
44. Qiao, L. *et al.* UAV-based chlorophyll content estimation by evaluating vegetation index responses under different crop coverages. *Comput. Electron. Agric.* **196**, 106775 (2022).
45. Han, C., Zhang, L. X. & Yue, M. T. GWR-model-based analysis of spatialtemporal evolution with its influencing factors of carbon emission intensity in Beijing-Tianjin-Hebei Counties. *J. Hunan Univ. Technol.* **37**(5), 68–77 (2023).
46. Tian, C., Cheng, L. & Yin, T. Spatial heterogeneity of driving forces in response to carbon emissions from land use at county-level in Beijing-Tianjin-Hebei Region. *Pol. J. Environ. Stud.* **32**, 267–279 (2022).
47. Chen, M., Gong, Y., Li, Y., Lu, D. & Zhang, H. Population distribution and urbanization on both sides of the Hu Huanyong line: Answering the Premier's question. *J. Geogr. Sci.* **26**, 1593–1610 (2016).
48. Yuan, Z., Ming, C., Zhi, Tang & Ziao, Mei. Urbanization, land use change, and carbon emissions: Quantitative assessments for city-level carbon emissions in Beijing-Tianjin-Hebei region. *Sustain. Cities Soc.* **66**, 102701 (2021).
49. Yan, H., Guo, X., Zhao, S. & Yang, H. Variation of net carbon emissions from land use change in the Beijing-Tianjin-Hebei Region during 1990–2020. *Land* **11**, 997 (2022).
50. Chao, W., Jin, Z., Fan, Z., Wei, L. & Twumasi-Ankrah, M. J. Analysis of urban carbon balance based on land use dynamics in the Beijing-Tianjin-Hebei region, China. *J. Clean. Prod.* **281**, 125138 (2021).
51. Zhong, X., Lu, Y. & Zhong, Z. Did regional coordinated development policy mitigate carbon emissions? Evidence from the Beijing-Tianjin-Hebei region in China. *Environ. Sci. Pollut. Res.* **30**, 108992–109006 (2023).
52. Kim, K.-H. *et al.* Progress in the reduction of carbon monoxide levels in major urban areas in Korea. *Environ. Pollut.* **207**, 420–428 (2015).
53. Yang, L. & Li, Z. Technology advance and the carbon dioxide emission in China—empirical research based on the rebound effect. *Energy Policy* **101**, 150–161 (2017).
54. Ying, F., Lan, L., Gang, W. & Yi, Wei. Analyzing impact factors of CO₂ emissions using the STIRPAT model. *Environ. Impact Assess. Rev.* **26**, 377–395 (2006).

Author contributions

L.Z. conceived the experiment(s). D.Y. and L.Z. conducted the experiment(s), Y.F. and R.Y. Data analysis. D.Y. and L.Z.: original draft writing, Y.F. and R.Y.: original draft review and editing. All authors contributed to this article and approved the submitted version.

Funding

This study was supported by the National Natural Science Foundation of China (No. 52174160).

Competing interests

The authors declare no competing interests.

Additional information

Correspondence and requests for materials should be addressed to L.Z.

Reprints and permissions information is available at www.nature.com/reprints.

Publisher's note Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.

Open Access This article is licensed under a Creative Commons Attribution-NonCommercial-NoDerivatives 4.0 International License, which permits any non-commercial use, sharing, distribution and reproduction in any medium or format, as long as you give appropriate credit to the original author(s) and the source, provide a link to the Creative Commons licence, and indicate if you modified the licensed material. You do not have permission under this licence to share adapted material derived from this article or parts of it. The images or other third party material in this article are included in the article's Creative Commons licence, unless indicated otherwise in a credit line to the material. If material is not included in the article's Creative Commons licence and your intended use is not permitted by statutory regulation or exceeds the permitted use, you will need to obtain permission directly from the copyright holder. To view a copy of this licence, visit <http://creativecommons.org/licenses/by-nc-nd/4.0/>.

© The Author(s) 2024