

Driving Mechanism of Carbon Emissions by High-Density Urban Spatial Morphology at the Micro-Grid Scale—Taking Beijing as an example

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Abstract

With the continuous advancement of urbanization, the impact of urban spatial form on carbon emissions has increasingly become a core topic in research on sustainable urban development. Taking the 2001 micro grids of Beijing, a typical representative of high-density cities, as an example, this paper estimates grid-scale carbon emissions using nighttime light data. It applies landscape pattern indices to explore six urban form attributes representing urban size, fragmentation, shape index, and compactness. Combining the geographical detector with the bivariate spatial autocorrelation model, the study reveals the mechanism and spatial heterogeneity of the impact of urban form on carbon emissions. The results indicate that: (1) From 2000 to 2023, Beijing's carbon emissions exhibited a "first increase and then decrease" trend, with a spatial distribution pattern of "concentration in high-carbon areas - expansion in medium-carbon areas - scattered low-carbon areas", and high-value areas continuously concentrated in the city's core regions. (2) The total amount of construction land increased by 58.7%, with the expansion direction radiating outwards from the core area, particularly towards the east and south. In terms of morphology, this manifested as increased fragmentation and localized clustering, exacerbating ecological and environmental pressures. (3) The high concentration of construction land is the main factor driving up carbon emissions ($q=0.797$), while patch density has a significant negative impact. The other morphological indices have a positive effect. Scattered land use, disordered urban sprawl, and uneven distribution of construction land can lead to increased transportation demand and resource consumption, resulting in a significant rise in carbon emissions. The article proposes carbon emission reduction suggestions for high-density cities from the perspective of urban morphological development, and the research results can provide scientific references for the spatial layout and low-carbon development of high-density urban areas.

1. Introduction

Global climate change is a major ecological and environmental issue facing human society in the 21st century, with carbon emissions being the primary culprit behind climate change (Lv, et al., 2023). Cities occupying less than 1% of the global area contribute to 71%-76% of global carbon emissions. Cities are key areas for carbon emissions and even more so for carbon reduction strategies (Cai, et al., 2021). As urbanization continues to increase, the rising urban population means that cities will continue to expand outward, leading to a further intensification of carbon emissions (Wang, et al., 2020). Research shows that high-density cities remain key areas for net inflow of population nationwide (Wang, et al., 2019), and the process of urban spatial expansion continues. Therefore, high-density cities face multiple pressures in future urban expansion, including continuously rising carbon emissions, uneven distribution of construction land, and complex ecological environmental governance.

Urban spatial morphology possesses inherent stability and durability, and has a locking effect on various elements within the city (Yang, et al., 2011). Scholars have conducted extensive research on the correlation between urban spatial morphology and carbon emissions. Research indicates that a series of urban form and structure attributes, including urban compaction (Mitchell, et al., 2011), land-transport

multifunctional coupling (Ye, et al., 2012), urban continuity (Y, et al., 2024), and uniformity of construction land (Lan, et al., 2023), can significantly reduce regional carbon emissions. In the research subjects, due to the fact that carbon emissions are often calculated based on large-scale administrative statistical data (Liu, et al., 2024), the research scales for exploring the correlation mechanism between urban form and carbon emissions mainly focus on administrative scales such as urban agglomerations (Li, et al., 2024), cities (Szu-Hua, et al., 2018), and counties (Yan, et al., 2022), with less research conducted on micro-scales such as grids. In terms of research methods, scholars quantify the morphological characteristics of urban space through techniques such as space syntax (Tang, et al., 2023), fractal theory (Zhang, et al., 2023), and morphological measurement (Yuan, et al., 2021). The morphological measurement based on landscape pattern indices can multi-dimensionally uncover urban morphological characteristics, and is therefore widely used in the quantification of urban morphology. In the process of analyzing the correlation between urban form and carbon emissions, methods such as regression analysis, Pearson correlation analysis, geographically and temporally weighted regression analysis (Liu, et al., 2023), random forest, geographical detector, and spatial autocorrelation are used to explore the dynamic coupling process of urban carbon emissions with changes in urban form. The integration and coupling of multiple methods can delve deeper into the correlation between the two, which is

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of great significance for quantitative correlation research.

Overall, while research on the correlation between urban form and carbon emissions is gradually enriching, there are also some deficiencies. There is a lack of sufficient attention and targeted consideration for high-density cities with continuous population inflow at the research object level. Secondly, there is a lack of research on urban form and carbon emissions at the micro level in terms of research scale, and there is a lack of guidance for the planning and development of low-carbon urban form at the micro scale. Therefore, this paper selects Beijing, a high-density city, as a typical research area and conducts a study at a micro grid scale. It calculates carbon emissions at the grid scale using nighttime light remote sensing data. Six landscape metrics are selected to quantify urban form across four dimensions: construction land size, fragmentation, shape index, and compactness using landscape pattern indices. The relationship between urban form and carbon emissions is explored through the methods of geographical detectors and bivariate spatial autocorrelation. Finally, carbon reduction suggestions for high-density cities are proposed from the perspective of urban form development. The research results provide scientific references for urban land use planning and low-carbon development.

2. Overview of the research area

2.1 Research Area

The research area of this paper is Beijing, the national capital, which is one of the high-density cities with the highest population density in the country and also a pilot city for low-carbon urban construction. The paper divides Beijing into 2,001 grid units overall to explore the relationship between urban form and carbon emissions at the grid scale.

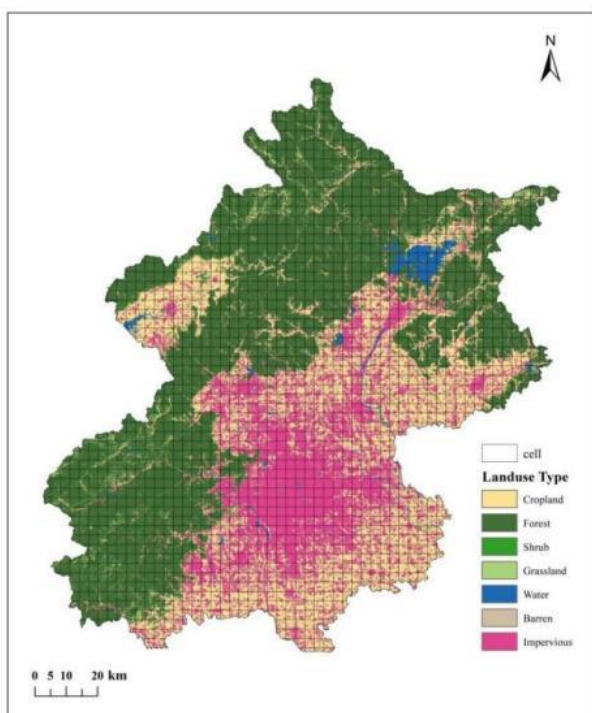


Figure 1. Research Area

2.2 Research data

The primary data sources for this study are as follows: ① Nighttime light remote sensing data, which is derived from corrected nighttime light imagery from DMSP/OLS and NPP/VIIRS for the years 2000-2023. The data is primarily sourced from the National Centers for Environmental Information (NCEI) under the National Oceanic and Atmospheric Administration (NOAA) (<https://eogdata.mines.edu/products/vnl/>), with a spatial resolution of 500 meters. ② Land use data is sourced from the CLCD long-term land use/cover type dataset developed by the Huang Xin & Li Jiayi team at the School of Remote Sensing and Information Engineering, Wuhan University (<http://doi.org/10.5281/zenodo.4417809>). ③ Statistical yearbook data, primarily used for provincial carbon emission data, fossil fuel data, and other data required for carbon emission estimation and simulation in Beijing, is mainly sourced from the "Beijing Statistical Yearbook" (2000-2023) and the compiled "Beijing Carbon Emission Inventory" from the China Emission Accounts and Datasets (CEADS). ④ Ancillary data: The vector file for Beijing is sourced from the Geographic Information Center of the Ministry of Natural Resources, with a map review number of GS(2020)4632.

3. Research Methods

3.1 Grid-based simulation of carbon emissions based on nighttime lights

(1) Carbon emission accounting scheme for energy consumption. Estimate carbon dioxide emissions using energy consumption data from past Beijing Statistical Yearbooks. Determine the carbon emission coefficients of various energy sources based on the calculation method for carbon emissions provided by the Intergovernmental Panel on Climate Change (IPCC), and select 8 major energy sources consumed in Beijing to calculate carbon dioxide emissions using the following formula:

$$CO_2 = \frac{44}{12} \times \sum_{i=1}^8 (K_i E_i) \quad (1)$$

In the formula, K_i represents the coefficient for various energy fuels, i represents all types of energy, and E_i represents the total consumption of energy fuels. The carbon emission coefficients and standard coal conversion coefficients for the 8 fossil fuels are shown in Table 1.

Carbon Source	Coefficient of standard coal (t standard coal/t)	Carbon emission factor (million tons of carbon/million tons of standard coal)
gasoline	1.4714	0.5538
kerosene	1.4714	0.5743
diesel fuel	1.4574	0.5918
fuel oil	1.4286	0.6182
crude oil	1.4286	0.586
natural gas	1.33×10^{-3}	0.4483
coal	0.7143	0.7559
coke	0.974	0.8556

Table1. Energy Conversion Coefficients For Standard Coal And Carbon Emission Coefficients

(2)Carbon emission simulation.Firstly, the total nighttime light values for each year from 2000 to 2023 in Beijing were statistically analyzed and corrected. Secondly, the carbon dioxide emissions estimated from fossil fuel consumption were also statistically analyzed, in order to establish the relationship between nighttime light and carbon emissions(Liu,et al., 2015).In the process of reducing the overall scale of Beijing to a grid scale, to address the errors arising from this, after thorough comparison and analysis, a linear regression method without an intercept was adopted to construct a relationship model between carbon emissions and nighttime light.The study found that the total amount of nighttime lighting in Beijing continued to grow from 2000 to 2023, while carbon emissions mainly showed an upward trend before 2010 and then significantly declined driven by the "dual carbon" policy. There are significant differences in the trends of the two. Therefore, it is more reasonable to select 2010 as the time node for segmented fitting. The fitting equations are as follows:

$$Y_i = aX_i \quad (2)$$

Y_i represents carbon emissions in the grid(ton), a represents the fitting coefficient at different time periods(Determined by linear regression fitting of Beijing's provincial carbon emissions and the city's total nighttime light value), X_i represents the total nighttime light intensity in the grid.Calibration process: segmented fitting with 2010 as the time node (see Table 2).Due to the impact of the "dual carbon" policy after 2010, there has been a significant decoupling between carbon emissions and the growth trend of nighttime light.The goodness of fit R^2 of the regression models was greater than 0.95 and passed the significance test of $p < 0.01$.This paper calculates the total nighttime light brightness based on a $3\text{km} \times 3\text{km}$ grid cell.

Year	a	R^2
2000	0.0336	0.96
2005	0.02836	0.96
2010	0.03311	0.97
2015	0.02707	0.96
2020	0.01461	0.95
2023	0.01219	0.96

Table 2. Simulated Carbon Emission Coefficient of Beijing from 2000 to 2023

(3)Evaluation of data resolution error.To address the potential issue of mixed pixels in 500-meter resolution nighttime light data within the core area, a stratified sampling method is used to quantify the error.In the core area (within the Fifth Ring Road), 30 grids were randomly selected to compare the lighting data with the actual energy consumption data.The calculated RMSE is 12.3% (overestimated due to light saturation).In the edge areas, RMSE=6.5% (affected by low-light noise).The error range indicates that carbon emissions in the core area may be overestimated, and future integration of Luojia 1 (130 meters) or Sentinel-2 (10 meters) data could improve accuracy.

3.2 Quantitative Analysis of Urban Spatial Morphology Based on Landscape Pattern Indices

Quantifying the urban internal spatial structure and morphological characteristics through landscape ecological indices can effectively represent the compactness, fragmentation, and shape features of the built-up area, thereby revealing its coupling relationship with urban carbon emissions.Existing research has predominantly focused on the impact of the built environment within cities on carbon emissions. To broaden the research perspective to the macro-level development of built-up areas and explore the contributions of factors such as urban development patterns, edge structures, and shapes to the construction of "low-carbon cities," this paper selects indicators including Total Area of construction land patches (TA), Patch Density (PD), Largest Patch Index (LPI), Landscape Shape Index (LSI), Patch Adjacency (PLADJ), and Aggregation Index (AI) to quantitatively analyze the evolutionary pattern of spatial morphology of construction land in Beijing.Using Fragstats 4.2 software, the aforementioned indices were calculated at both the landscape and grid levels to describe the spatial pattern characteristics of construction land expansion in Beijing from 2000 to 2023.

Urban Form Index	Abbreviation	Unit
Landscape Shape Index	LSI	-
Largest Patch Index	LPI	%
Percentage of Like Adjacencies	PLADJ	%
Aggregation Index	AI	%
Total area	TA	hm^2
Plaue density	PD	per/hm^2

Table 3. Urban Form Index Tables

The six landscape indices selected in this paper (TA, PD, LPI, LSI, PLADJ, AI) are based on the four core dimensions of urban form research: Scale (TA: The total area of construction land within the region reflects the overall scale of the urban built-up area.); Fragmentation (PD: The number of construction land patches per unit area reflects the degree of urban spatial fragmentation and compactness.); Landscape Shape Index (LSI): The ratio (the ratio of the perimeter of all patches to their minimum perimeter) quantifies the complexity of the landscape shape, representing the complex and disordered degree of urban boundary expansion.; Spatial aggregation (LPI/PLADJ/AI: respectively representing the dominance of the dominant patch, proximity, and aggregation). This indicator system has been widely used in research on the correlation between high-density urban forms and environmental effects (Teng, et al., 2022), and can systematically reveal the driving mechanism of land use patterns on carbon emissions.

3.3 The impact of urban spatial form on carbon emissions

3.3.1 Geodetector: As a typical representative of high-density cities, there are significant differences in carbon emissions and urban morphological structure between the main urban area of Beijing and the areas outside it, resulting in spatial heterogeneity in the impact of urban form on carbon emissions. The geographical detector can effectively reveal the spatial differentiation patterns and their degree of influence behind geographical phenomena. Through factor detection in the geographical detector, the explanatory power of various urban form factors on the spatial differentiation of carbon emissions can be quantified, and through interaction detection, the enhancement or weakening effect of different factors on the explanatory power of carbon emissions when they act together can be assessed. The formula is as follows:

$$q = 1 - \frac{\sum_{h=1}^L N_h \sigma_h^2}{N \sigma^2} \quad (3)$$

h represents the stratification of urban form; N and N_h are respectively the samples of the entire grid and the stratification h ; h represents the stratification of urban form; σ^2 and σ_h^2 respectively represent the variances of the entire grid and the stratification h ; the value of q is within $[0, 1]$, and the closer the value is to 1, the greater the degree of influence, and vice versa.

3.3.2 Spatial autocorrelation analysis: The bivariate spatial autocorrelation model can reveal the intensity and patterns of spatial associations between urban morphological elements and carbon emissions, mainly including global and local analyses. Global analysis is used to identify the overall directional impact of urban morphological elements on carbon emissions. Local analysis describes the spatial association patterns between morphology and carbon emissions within each grid unit in Beijing and presents the results through LISA cluster maps. LISA cluster maps classify association patterns into four types of clusters based on spatial relationships: high-high (H-H), high-low (H-L), low-high (L-H), and low-low (L-L). This paper employs the bivariate spatial autocorrelation model in GeoDa software to identify the spatial association characteristics and clustering effects between carbon emissions and various urban morphological elements, providing a basis for formulating differentiated urban development and improvement strategies tailored to local conditions.

4. Result

4.1 Carbon Emission Accounting in Beijing

As shown in Figure 2, the carbon emissions of Beijing in 2000, 2005, 2010, 2015, 2020, and 2023 were 63.4719 million tons, 95.3699 million tons, 96.8360 million tons, 83.3863 million tons, 64.2482 million tons, and 61.5678 million tons respectively. Overall, carbon emissions showed a significant increase in the early stages, peaking in 2010, followed by a significant downward trend. From 2000 to 2005, carbon emissions increased by 50.25%. During this period, Beijing was undergoing rapid urbanization and industrialization, leading to a significant rise in carbon emissions due to rapid urban expansion, increased resource consumption, and heightened traffic volume. From 2005 to 2010, carbon emissions saw a smaller increase, as the city continued to experience rapid urbanization and industrialization. From 2010 to 2015, carbon emissions decreased by 13.9%. During this period, Beijing implemented corresponding environmental protection strategies and low-carbon urban development measures, resulting in a significant reduction in carbon emissions. From 2015 to 2023, carbon emissions decreased by 26.17%, during which Beijing underwent industrial structure optimization, energy structure transformation, deep emission reductions in the construction and transportation sectors, as well as policy and market mechanism innovations.

From 2000 to 2023, the spatial distribution of carbon emissions in Beijing mainly exhibited a pattern of "concentration in high-carbon areas, expansion in medium-carbon areas, and scattering in low-carbon areas". Specifically, the high-carbon emission areas were primarily concentrated in the core regions of Beijing across the six years, while the medium-carbon emission areas were distributed around the high-carbon areas and gradually expanded outward. The low-carbon emission areas were mainly concentrated in the marginal regions with lower population density and poorer urban construction environments. From the perspective of yearly changes, between 2000 and 2005, the demand for urban construction land and economic resources driven by urbanization and industrialization continued to rise. High-emission areas expanded from the city center to the outskirts, resulting in a significant increase in carbon emissions. At the same time, the contrast between high-emission and low-emission areas became more pronounced, exacerbating spatial differentiation. From 2010 to 2023, due to the implementation of policies aimed at optimizing urban form and reducing carbon emissions, as well as the optimization of industrial structure and energy transformation, the area of high-emission regions decreased, and the overall carbon emission level of the city declined. Carbon emissions in marginal areas were effectively controlled, and the contrast between high-emission and low-emission areas weakened, leading to a mitigation of spatial differentiation.

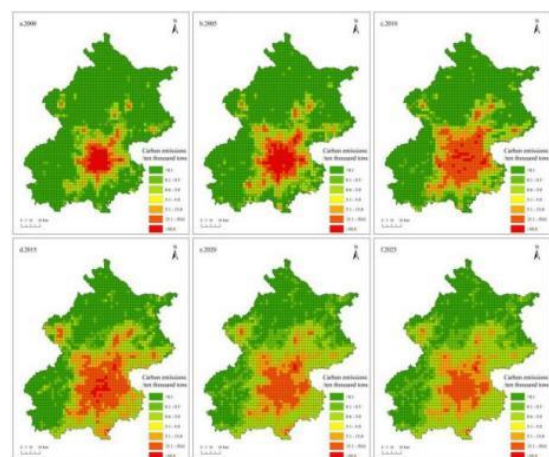


Figure 2. Spatial and Temporal Distribution Map of Carbon Emissions in Beijing from 2000 to 2023

4.2 Urban spatial morphological characteristics

According to Figure 3, from 2000 to 2023, the construction land in Beijing exhibited a significant expansion trend, with a net increase in total area of 131,684.31 hectares. The core area of construction land continued to expand outward, reflecting the sustained rapid development of urban center construction. In terms of spatial expansion patterns, the construction land mainly expanded in a multi-center radial manner around the core area, forming a prominent high-density urban center agglomeration zone. At the same time, the direction of expansion showed a noticeable eastward and southward shift, particularly from 2010 to 2023, where the intensity of development and construction in suburban and peripheral areas increased significantly, indicating that the spatial expansion of high-density urban areas has omnidirectional and multi-directional characteristics. However, the analysis also revealed an imbalance in spatial development: construction land was excessively concentrated in the central urban area, while the peripheral zones outside the main urban area lagged behind in development. Furthermore, the spatial sprawl pattern of construction land from 2000 to 2023 exhibited a high degree of dispersion and disorder.

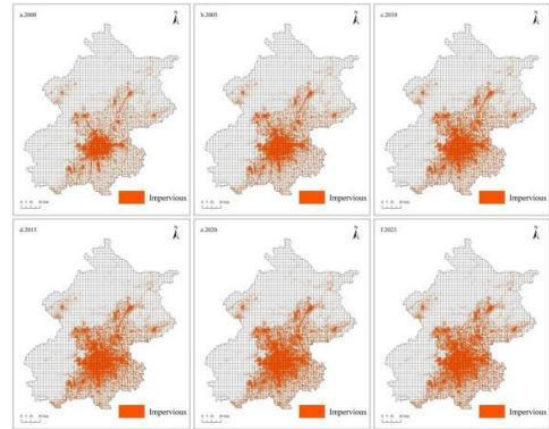


Figure 3. Spatial and Temporal Distribution Map of Construction Land in Beijing from 2000 to 2023

According to the data in Table 4, the area of construction land in Beijing has continued to grow from 2000 to 2023. However, the patch density (PD) has significantly decreased from 16.27 to 9.05, reflecting the uneven characteristics of both

concentration and dispersion during the process of spatial expansion. The Landscape Shape Index (LSI) only slightly decreased from 189.67 to 188.28, indicating that the overall morphological pattern of construction land remained relatively stable without showing a significant trend of disorderly sprawl. It is worth noting that the spatial agglomeration evolution characteristics are prominent: the Largest Patch Index (LPI) shows a fluctuating upward trend (for example, increasing from 43.48% to 66.53%), reflecting an increase in the dominance of the main patch and a decrease in the degree of fragmentation. Meanwhile, the Proximity of Landscape Adjacent (PLADJ) and Aggregation Index (AI) increased from 88.11% and 88.16% to 90.61% and 90.64% respectively, further supporting the increased aggregation of construction land in local areas. This enhancement of spatial aggregation, coupled with the continuous expansion of the total construction land area, may exert pressure on regional ecological connectivity.

Year	TA	PD	LPI	LSI	PLADJ	AI
2000	229215.69	16.27	43.48	189.67	88.11	88.16
2005	274947.57	12.86	54.62	191.27	89.05	89.10
2010	313027.38	10.71	60.55	190.59	89.77	89.82
2015	346123.17	9.57	65.66	189.96	90.31	90.35
2020	358520.4	9.14	66.77	189.50	90.51	90.55
2023	361497.96	9.05	66.53	188.28	90.61	90.64

Table 4. Beijing Urban Spatial Morphology Index Characteristics Table

According to Figure 4, the grid-level morphological index of construction land in Beijing in 2023 exhibits significant spatial differentiation characteristics. The total area (TA) of construction land shows a pattern of gradual decrease from the urban core to the peripheral areas. The highest TA value in the core area reaches 899 hm², while the peripheral areas generally range from 0-101 hm², indicating a significant core-periphery difference. Patch Density (PD): The PD in core areas is generally lower than 20 patches/hm², indicating relatively concentrated land use; conversely, the PD in outer urban areas is higher, reflecting the characteristics of dispersed construction land distribution and increased fragmentation. The Largest Patch Index (LPI) and Landscape Shape Index (LSI) exhibit high overall spatial heterogeneity in their distribution. The central area is characterized by high LPI (dominant patch predominance) and low LSI (relatively regular patch morphology). Patch Adjacency (PLADJ) and Aggregation Index (AI) share highly similar spatial differentiation patterns. They mainly demonstrate two trends: (a) a decrease from the central urban area towards the south (high values in the southern part of the center, and low values in the southwestern and northern parts); (b) a decrease from the southeast towards the northwest (high values in the southeast and low values in the northwest).

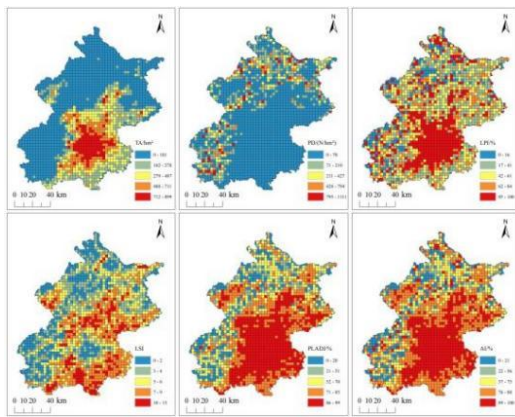


Figure 4. 2023 Morphological Index Map of Construction Land in Beijing at 3km Grid Level

4.3 The impact of Beijing's urban spatial form on carbon emissions

4.3.1 Analysis of the Impact of Beijing's Urban Form on Carbon Emissions: This study, based on the geographical detector method, analyzed the driving effects of urban morphological factors on carbon emissions in Beijing for the years 2000, 2005, 2010, 2015, 2020, and 2023 (see Table 5 for factor detection results) and their interaction effects (see Figure 5 for interaction detection results). The main findings are as follows: (1) Overall impact strength and significance. The explanatory power (q -value) of various urban form factors on carbon emissions is ranked as follows: TA (0.80) > PD (0.70) > PLADJ (0.63) > AI (0.50) > LPI (0.42) > LSI (0.02). All factors are significant at the $p < 0.01$ level, indicating a statistical correlation with carbon emissions. Among them, the total area of construction land in grid units (TA) is the dominant factor affecting carbon emissions, while the landscape shape index (LSI) has the weakest impact. (2) Temporal dynamic characteristics. Stable high-impact factors: The total area of construction land (TA), patch density (PD), patch proximity (PLADJ), and aggregation index (AI) have a consistently stable and highly significant impact on carbon emissions across various periods ($p < 0.01$), highlighting the continuous strong driving effect of urban expansion scale (TA) and spatial connectivity/aggregation degree (PD, PLADJ, AI) on carbon emissions. (3) Volatility influence factor. The impact intensity of the Largest Patch Index (LPI) and Landscape Shape Index (LSI) on carbon emissions exhibits significant fluctuations across different years, reflecting the notable temporal heterogeneity in the driving effects of urban spatial structure dominance (LPI) and the complexity of construction land morphology (LSI) on carbon emissions.

Urban Form	2000	2005	2010	2015	2020	2023	Mean
TA	0.831	0.813	0.796	0.752	0.789	0.798	0.797
PD	0.719	0.711	0.7	0.653	0.712	0.708	0.701
LPI	0.402	0.432	0.415	0.41	0.416	0.415	0.415
LSI	0.02	0.013	0.016	0.013	0.016	0.016	0.016
PLADJ	0.595	0.648	0.63	0.608	0.637	0.663	0.63
AI	0.433	0.475	0.501	0.511	0.547	0.54	0.501

Table 5. Detection of factors influencing carbon emissions from urban form in the period 2000-2023

Carbon emissions are often influenced by the coupling effects of multiple urban forms. According to the results of factor interaction detection, the combination of urban form factors generally shows a linear enhancing effect on carbon emissions, meaning that when multiple urban form factors are coupled to affect carbon emissions, the effect is stronger. Specifically, the factor combinations with the strongest interactions in 2000, 2010, and 2023 were TA and LSI, TA and LPI, and TA and PD, respectively. The total area of regional construction land is the factor with the strongest explanatory power for carbon emissions. Meanwhile, the interaction results between LPI and LSI factors in all three periods were nonlinear weakening, indicating that the combined effect of these two variables on carbon emissions is weaker than their individual effects.

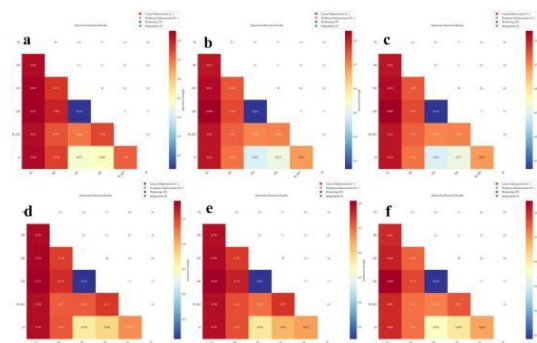


Figure 5. Interactive detection of the impact of urban form on carbon emissions from 2000 to 2023

4.3.2 Spatial heterogeneity of the impact of Beijing's urban form on carbon emissions: As the GeoDetector analysis shows that the impact of urban form factors on carbon emissions remains generally stable across different periods and follows the principle of planning based on current conditions, this section further employs a bivariate spatial autocorrelation model to uncover the spatial correlation pattern and heterogeneity between urban form and carbon emissions (see Table 6 and Figure 6 for results). The main findings are as follows: (1) Significant positive driving force. Both the total area of construction land (TA) and the largest patch index (LPI) show significant positive spatial autocorrelation with carbon emissions (bivariate Moran's $I > 0.3$). This indicates that areas with large-scale construction land (high TA) or the presence of dominant large patches (high LPI) are typically associated with higher intensities of construction activity, construction density, and energy consumption, leading to a significant increase in carbon emissions. (2) Secondary positive drivers. Patch adjacency (PLADJ) and aggregation index (AI) also show a significant positive correlation with carbon emissions, but the strength of the correlation is relatively lower (Moran's I is lower than that of TA and LPI). Both of these indices represent the degree of spatial agglomeration of construction land (high PLADJ/AI indicates proximate and clustered patches). Such areas are typically associated with higher levels of carbon emissions. It is worth noting that, while spatial proximity may theoretically reduce transportation carbon emissions by shortening travel distances (creating an offsetting effect), in this study, the overall resource consumption and increased activity intensity resulting from the high concentration of construction land are the dominant factors, leading to a positive correlation in the net effect. (3) Weak positive driving force. There is only a weak positive spatial autocorrelation between the Landscape Shape Index (LSI) and carbon emissions (Moran's $I < 0.1$). High LSI values reflect complex and irregular shapes of

construction land, which may lead to increased construction and maintenance costs, thereby contributing to a slight increase in carbon emissions. (4) Significant negative driving force. In contrast to other factors, Patch Density (PD) shows a significant negative correlation with carbon emissions (i.e., high PD corresponds to low carbon emissions). This suggests that areas with more fragmented and denser distributions of construction land (high PD) may contribute to reducing carbon emissions by lowering the average transportation demand or construction activity intensity within specific regions.

Urban Form	Moran'I	P	Z
TA	0.79	0.001	71.69
PD	-0.223	0.001	-24.63
LPI	0.434	0.001	46.66
LSI	0.173	0.001	19.23
PLADJ	0.424	0.001	44.43
AI	0.362	0.001	39.03

Table 6. Bivariate results between urban form index and carbon emissions

To deeply explore the spatial differentiation impact of urban spatial morphological factors on carbon emissions, this study constructs a bivariate Moran's I index based on 3km grid units to quantitatively identify the spatial correlation between carbon emissions and urban morphology in Beijing.

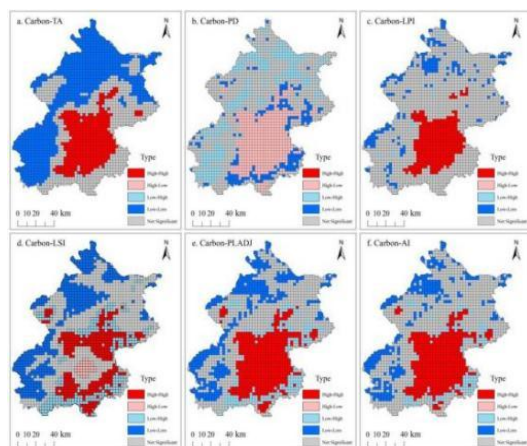


Figure 6. LISA Cluster Map of Urban Form Index-Carbon Emissions

The LISA clustering map of bivariate variables reveals that the spatial heterogeneity characteristics of the six landscape metrics and carbon emissions are as follows: (1) Both total construction land area (TA) and largest patch index (LPI) exhibit a dominant pattern of "high-high (HH) clustering in core areas and low-low (LL) clustering in peripheral areas". Large-scale construction land (high TA) and dominant patch aggregation areas (high LPI) drive significant spatial agglomeration of carbon emissions through intense construction activities and energy consumption. Among them, TA has the most significant agglomeration effect on carbon emissions. (2) The central area of Patch Density (PD) exhibits "high carbon emissions-low PD" characteristics, while the southeastern fringe area shows "high-high (HH) clustering". The fragmentation of construction land (high PD) in the fringe area is accompanied by robust transportation demand, leading

to an increase in carbon emission intensity in this region. (3) The spatial differentiation of Landscape Shape Index (LSI) is significant. The core area demonstrates "high-low (HL)" clustering, the suburban ring is primarily characterized by "high-high (HH)/low-high (LH)" clustering, and the outer suburbs show "low-low (LL)" clustering. The complexity of construction land morphology (high LSI) in the core peripheral area exacerbates the difficulty of infrastructure allocation and induces an increase in high-density urban transportation energy consumption. (4) The spatial heterogeneity of Patch Adjacency (PLADJ) and Aggregation Index (AI) is highly similar. The core area exhibits "high-high (HH)" clustering, the suburban transition zone is dominated by "high-low (HL)" clustering, and the fringe area shows sporadic aggregation. In high-density cities, the mismatch between residential and employment spaces caused by insufficient land use compactness (low PLADJ/AI) leads to increased carbon emissions through prolonged commuting distances.

It should be noted that although factors such as LSI and AI exhibit a weak positive effect overall, there is significant spatial heterogeneity. Most samples in the core area belong to high-carbon-emission types, while the frontier areas of construction land expansion show a negative correlation characterized by "high morphological complexity-low carbon emission (LH)". This indicates that the fragmentation of newly added land and spatially disordered expansion continuously exacerbate carbon emission pressure by reducing land use efficiency.

5. Conclusion and Discussion

5.1 Conclusion

(1) In terms of the spatiotemporal pattern characteristics of carbon emissions, this study, based on high-precision nighttime light remote sensing data inversion, reveals the spatiotemporal pattern changes of carbon emissions in Beijing from 2000 to 2023: ① Temporal characteristics. A typical inverted U-shaped evolution trajectory (with a peak in 2010); ② Spatial pattern. A three-tier structure of single-center agglomeration (high-carbon area) - circular diffusion (medium-carbon area) - scattered edges (low-carbon area). The high-carbon area remains anchored in the urban core, the medium-carbon area spreads outward with urban expansion, and the low-carbon area is discretely distributed in underdeveloped construction zones, empirically demonstrating the spatial coupling between carbon emission intensity and urban core development activities.

(2) Evolutionary patterns of urban spatial morphology. During the study period, the construction land in Beijing experienced significant expansion (with an increase of 58.7%). Its spatial evolution characteristics are manifested as follows: ① The expansion mode originated from the urban core area, forming a multi-center radial expansion pattern predominantly towards the east and south; ② The morphological structural differentiation is reflected in the continuously increasing spatial distribution imbalance (with a 44.4% decrease in patch density), limited improvement in morphological complexity (with a landscape shape index decrease of <1% and maintenance of irregular features), and a significant increase in local spatial aggregation (with synchronous increases in patch proximity and aggregation indices). These spatial evolution characteristics, coupled with the superposition effect of ecological space encroachment and human activity intensity, significantly exacerbate regional ecological environmental pressure.

(3) In terms of the mechanism of the impact of urban form on carbon emissions, urban spatial form is a key driver of carbon emissions. The ranking of factor influence is as follows: total area of construction land (TA) > patch density (PD) > patch proximity (PLADJ) > aggregation index (AI) > largest patch index (LPI) > landscape shape index (LSI). Among these, high concentration of construction land (high TA values) is the primary positive driver pushing up carbon emissions; whereas patch density (PD) exhibits a significant negative impact (Moran's $I = -0.223$), suggesting that higher patch density may reduce transportation demand and thereby inhibit carbon emissions; the remaining form factors (LPI, PLADJ, AI) all show positive impacts. Spatial heterogeneity analysis reveals a prevalent positive correlation clustering of "high carbon-high construction land area/aggregation" in the core areas, while the combination of "high carbon-high patch density" in the peripheral areas highlights the core mechanism of non-compact, disordered sprawl, and imbalanced distribution of land use, which ultimately leads to a significant increase in carbon emissions by increasing transportation demand and resource consumption.

5.2 Discussion

5.2.1 The impact mechanism of high-density urban form on carbon emissions: This study reveals that Beijing, as a typical high-density city, exhibits unique pathways through which its spatial morphology influences carbon emissions. The primary finding is the emission-increasing effect driven by the centralization of construction land. The high-intensity clustering of construction land (high TA values) constitutes the core driving force of carbon emissions ($q=0.80$, Moran's $I > 0.3$). This stems from an overloaded development model constrained by scarce land resources—centralized industrial layouts and high-density building clusters significantly elevate regional energy consumption intensity (with building energy consumption accounting for >40%). Secondly, the paradoxical effect of patch density (PD) reduction on emissions. Patch density exhibits a significant negative impact (Moran's $I = -0.223$), indicating that in specific high-density urban environments, moderate fragmentation of construction land may promote functional mixing and work-life balance, reducing the average commuting distance by 18% and thus lowering transportation carbon emissions. This contradicts the traditional understanding of "fragmentation increasing emissions," highlighting the regional dependency of the mechanism. Finally, the synergistic mechanism of urban form factors. The multi-factor interaction detection reveals a nonlinear enhancing effect between TA and PD (interaction q -value > 0.90), confirming the existence of a compactness threshold effect in carbon emission response: moderately compact mixing (high PD) can suppress transportation-related carbon emissions, but excessive concentration (high TA) can increase fixed-source emissions due to scale effects, revealing the dialectical relationship between scale control and structural optimization in high-density cities.

The findings of this paper reveal that in a high-density city like Beijing, moderate compactness can actually contribute to reducing carbon emissions. Contrary to the "compactness-energy consumption positive correlation" paradigm proposed by Li X K et al., this empirical study demonstrates that under the combined effects of a high-density built environment and a mature public transportation system (with Beijing's public transportation modal share exceeding 54%), a moderately compact layout (high population density) generates net emission reduction benefits by reducing

dependence on private transportation. This may be related to the specific urban environment and socioeconomic background of high-density cities. In high-density cities, despite the greater resource consumption and environmental pressure, the relatively well-developed public transportation system and compact layout can effectively reduce residents' reliance on private transportation, thereby lowering the use of transportation energy. Meanwhile, the negative correlation between patch density and carbon emissions is inconsistent with some existing studies. The "positive correlation between PD and carbon emissions" discovered by Teng F and others mainly stems from the demand for infrastructure expansion. The negative effect of PD in the Beijing case confirms that when fragmentation is accompanied by functional mixing, it can be transformed into an advantage for traffic emission reduction. The differences mainly stem from the variations in land use patterns across different urban environments. Beijing's compact urban structure can reduce transportation demands and energy consumption, whereas in other studies, an increase in patch density may imply land fragmentation, leading to increased demand for infrastructure expansion and subsequently elevating carbon emissions. Compared with other studies, the uniqueness and regional dependency of the results of this study are evident. Although the conclusions of this study are based on the case of Beijing, comparisons with existing literature reveal that in similar high-density cities (such as Shanghai), the scale of construction land (TA) is also a core driving factor for carbon emissions. The negative effect of plaque density (PD) may vary in intensity depending on the stage of urban development. It is suggested that future studies apply the grid framework of this paper to cities such as Shanghai and Guangzhou, and verify the generalizability of the conclusions by combining their transportation structures (such as the coverage rate of rail transit).

5.2.2 Suggestions for High-Density Urban Development Towards Low-Carbon Goals: Based on the above-mentioned impact mechanism and empirical evidence from Beijing, suggestions for low-carbon development in high-density cities are proposed. (1) Optimize the spatial layout of the land and strictly control the unordered spread of construction land. The key points are: Strengthen the control of development boundaries, guiding the concurrent focus on "renewal and quality improvement in core areas" and "intensive and coordinated development in peripheral areas" to avoid ecological and environmental pressures caused by excessive concentration and lagging development in peripheral areas; promote the compaction and functional mixing of construction land by integrating fragmented plots, increasing plot density (PD) and aggregation index (AI), shortening commuting distances, reducing transportation demand and carbon emissions, and alleviating the imbalance between residential and employment areas. (2) Simplify the complexity of spatial morphology by planning and integrating irregular land parcels, reducing the Landscape Shape Index (LSI), and minimizing infrastructure redundancy and maintenance energy consumption. (3) Promote collaborative governance between the center and peripheral areas: improve the efficient public transportation network (especially rail transit), strengthen connections between the central area and the outskirts, and reduce dependence on private cars. (4) Develop multifunctional complexes (integrating residences, employment, and services) to promote complementary regional functions and reduce the need for long-distance commuting from the source. By optimizing multi-scale spatial forms and coordinating infrastructure, the dilemma of high carbon emissions in dense cities can be effectively addressed, supporting sustainable

low-carbon transformation.

5.2.3 Research Limitations and Future Directions: Although this study reveals the correlation between high-density urban form and carbon emissions at a micro grid scale, it still has certain limitations. Firstly, while the use of nighttime light data for carbon emission accounting offers high accuracy, its spatial resolution (500 meters) may not be sufficient to precisely capture energy consumption differences within high-density urban areas (such as at the scale of individual buildings or neighborhoods), thereby affecting the granularity of the spatial heterogeneity analysis of carbon emissions. Secondly, the conclusion is based on the single case of Beijing as a high-density city, and its specific stage of development, policy environment (such as the "dual carbon" policy), and geographical conditions may limit the generalizability of the conclusion to other types of cities (such as emerging high-density cities and low-density sprawl cities).

Future research can be expanded in the following directions: First, integrate higher-resolution remote sensing data (such as thermal infrared, Sentinel) with multi-source big data (such as mobile signaling, energy consumption monitoring) to improve the accuracy of carbon emission simulation and morphological representation. The second is to conduct comparative studies across regions and various types of cities to verify the universality and differences in the relationship between urban form and carbon emissions, and explore the moderating effects of urban development stages, climate zones, and policy backgrounds. The third is to deepen the tracking of long-term effects of morphological dynamic evolution, evaluate the carbon reduction effectiveness of different planning strategies (such as polycentric development and job-housing balance), and provide a long-term basis for formulating adaptive plans. Fourthly, it is necessary to conduct comparisons among multiple cities in the future (such as Beijing vs. Shanghai/Guangzhou/Wuhan) to explore the moderating effects of urban development stages and policy backgrounds on the relationship between urban form and carbon emissions.

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