Exploring Low-Carbon Urban Development at the Plot Scale: A Study of Carbon Emission Mechanisms and Empirical Exploration of Micro-Renovation for Emission Reduction

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Abstract
In response to global climate change, cities - as key spatial carriers of human activity - must refine governance strategies. Focusing on Nanjing's main urban area, this study integrates ODIAC global carbon emission data with multi-source big data and applies Multi-scale Geographically Weighted Regression (MGWR) and Geo-Detector models to analyze drivers of land-use carbon emissions. Results show that functional attributes, spatial forms and carrying capacity characteristics have a spatially heterogeneous impact on carbon emission intensity, with the carrying capacity factors contributing the most and about 60% of the influencing factors having significant synergistic effects. Based on this, a low-carbon planning strategy at the micro-plot level is constructed, and the carbon emission intensity of the plot in Liuhe District is reduced from 6.96 kg/m² to 6.38 kg/m², with an annual carbon emission reduction of 153 tons. This function-form-capacity collaborative control approach effectively reduces urban land-use carbon intensity and supports low-carbon city goals.

Keywords: Urban carbon emissions, Micro-perspective, Multi-scale geographically weighted regression model (MGWR), Geo-Detector, Low-carbon micro - renovation

1.Introduction

As global climate change intensifies, greenhouse gas emissions have become one of the major challenges faced by humanity. Cities, as areas of high population, economic, and social activity concentration, contribute approximately 70% to 80% of global carbon dioxide emissions (Kumar, 2007, Sun et al., 2022, Wang et al., 2023). Therefore, low-carbon urban development has become key to achieving the goals of carbon peak and carbon neutrality. China has proposed the "dual carbon" strategy, aiming to peak carbon emissions by 2030 and achieve carbon neutrality by 2060, which brings unprecedented pressure and opportunities for urban green transformation and planning (Shi, 2022). In this context, a deep scientific understanding of the temporal and spatial distribution characteristics of urban carbon emissions and their driving mechanisms has become the foundation for formulating precise and effective carbon reduction policies and achieving the construction of low-carbon cities.

Urban land, as the basic unit of urban space, aggregates elements such as population, industry, buildings, and transportation, and is the primary source of carbon emissions (Liu et al., 2025). Studies have shown that high-density and functionally mixed urban areas are more conducive to improving energy efficiency and reducing per capita carbon emissions compared to low-density, single-function zones (Zhang et al., 2022). Therefore, accurately grasping the carbon emission patterns at the urban land scale is the foundation for formulating low-carbon urban development strategies. However, most existing carbon emission studies primarily focus on urban or regional scales, using administrative divisions or grid units (Li et al., 2025, Liu and Zhao, 2023, Shen et al., 2023). While such studies can reveal the spatial distribution and evolution of carbon emissions from a macro perspective, their relatively coarse spatial resolution fails to reflect the differences and underlying mechanisms at the micro scale, limiting guidance for low-carbon strategies at specific plots or street block levels.

The research on the factors influencing carbon emissions is diverse. Many scholars start with macro-statistical variables such as population, industry, and energy structure, using tools such as Ordinary Least Squares (OLS), the STIRPAT model (Stochastic Impacts by Regression on Population, Affluence, and Technology) (Shahbaz et al., 2016, Zhou et al., 2015), and machine learning algorithms (Tian et al., 2024a)China (2009-2023 to analyze the driving mechanisms. Meanwhile, some studies have begun to focus on the internal spatial structure of cities, particularly the impact of land use types and spatial form on carbon emissions (Wang et al., 2025, Li et al., 2025). For instance, Wang et al. (2019), using Eindhoven City in the Netherlands as a case study, divided land functions into fourteen categories and analyzed the relationship between different land use types and urban carbon emissions, revealing the differential contribution of various functional land uses to carbon emissions.

However, existing studies mostly emphasize a single dimension or static analysis, lacking a systematic integration of multi-dimensional indicator systems to comprehensively explain the complex mechanisms of urban land carbon emissions.

In order to more comprehensively characterize the influencing factors of urban land carbon emissions, this study divides the attributes of urban land into three main categories: functional attributes, spatial form, and carrying capacity. Functional attributes encompass land use types and their proportions, reflecting the socio-economic functions of the land; spatial form includes physical characteristics such as building form, density, and number of stories, reflecting the organizational structure of urban space; carrying capacity represents the population scale, economic activity intensity, and traffic network density supported by the land, indicating the land's capacity and load level (Zhu et al., 2025, Li et al., 2021). This classification not only aligns with the practical logic of urban planning but also systematically reveals the driving paths of carbon emissions from different perspectives, providing a solid framework for subsequent in-depth analysis based on spatial statistical models.

In recent years, the introduction of spatial statistical tools such as Spatial Lag Model (SLM), Spatial Error Model (SEM), Spatial Durbin Model (SDM), Geographically Weighted Regression (GWR), and GeoDetector has effectively identified the spatial heterogeneity and interaction mechanisms of the factors influencing carbon emissions. For example, Wei et al. (2024) used the Spatial Durbin Model (SDM) to study the driving mechanisms of carbon emissions in China's urban agglomerations. Among them, Multi-scale Geographically Weighted Regression (MGWR) and GeoDetector models have gained increasing attention due to their ability to dynamically capture spatial variations in driving factors and multi-factor interactions (Rong et al., 2022, Zhang et al., 2025). The MGWR model captures the diverse driving mechanisms within regions by allowing variable coefficients to change with spatial location and scale. GeoDetector, on the other hand, identifies key influencing combinations by quantitatively analyzing the explanatory power of factors on spatial distribution and the interactions between factors.

Although existing studies have proposed low-carbon recommendations based on model results (Hurlimann et al., 2021, Woodruff et al., 2022), most lack quantitative evaluations linked to specific plots, making it difficult to verify the actual carbon reduction benefits of planning strategies at the micro spatial scale. Therefore, this study focuses on the micro-plot scale, applying both the MGWR and Geo-Detector models to systematically reveal the influence mechanisms and interactive effects of urban functional attributes, spatial form, and carrying capacity on carbon emissions, exploring their carbon reduction potential in specific plots. By combining empirical cases of micro-updating in typical plots of Nanjing's main urban area, this study quantitatively evaluates the performance of low-carbon planning interventions, filling the research gap on low-carbon micro-update performance evaluation, and providing strong support for the scientific formulation and implementation of precise low-carbon urban planning strategies.

2.Materials and Methods

2.1 **Study Area**

This study focuses on the main urban area of Nanjing as defined in the draft of the city's Land and Spatial Master Plan (2021-2035). The study area is delimited based on natural water systems and major road networks, covering a continuous urban space with a total area of approximately 970 square kilometers (see Figure 1). According to data from the China Carbon Accounting Database (Shan et al., 2017), the annual total carbon dioxide emissions in Nanjing reach 170.39 million tons, ranking second in Jiangsu Province. The choice of the main urban area as the study area encompasses not only the core region of urban development but also typical urban land use structures and carbon emission characteristics, making it both representative and valuable for research.

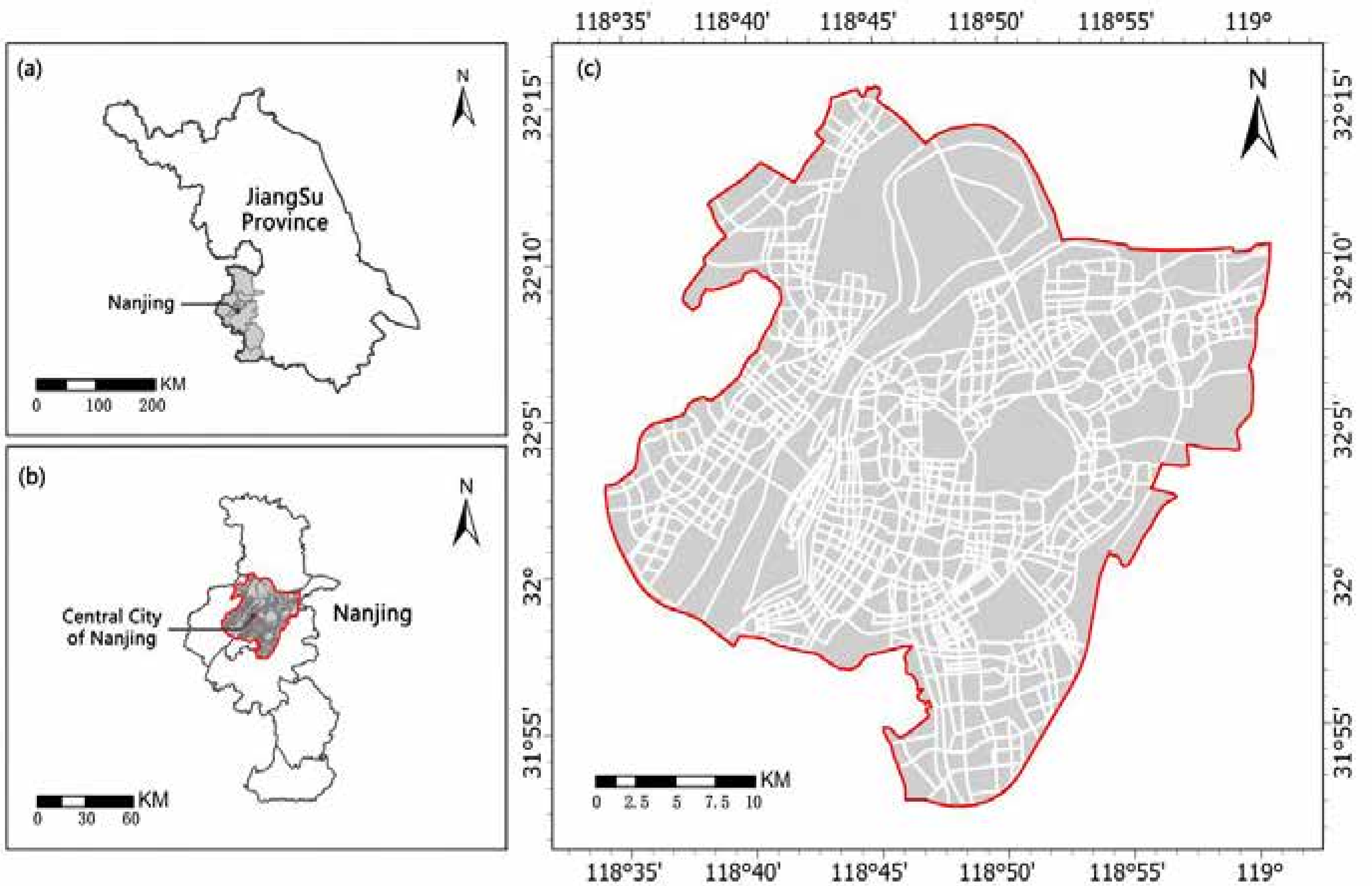


Fig. 1 Study area

2.2 Data Source

The carbon emission data used in this study is sourced from the ODIAC (Open-source Data Inventory for Anthropogenic CO2) global dataset, which is provided by the Center for Global Environmental Research (CGER). This dataset has a 1-kilometer spatial resolution. The data was clipped and regionally aggregated using ArcGIS software to extract the total annual carbon emissions for the main urban area of Nanjing in 2023, which serves as the dependent variable in this study.

The factor indicator system for carbon emissions was constructed with reference to numerous literature reviews and urban planning practices. It systematically integrates the key driving factors of carbon emissions from three dimensions: the functional attributes, spatial form, and carrying capacity of urban land. The functional attributes mainly reflect the nature and proportion of land use; spatial form indicators reflect building characteristics; and carrying capacity reflects the development intensity and spatial carrying capacity of the land. To avoid multicollinearity interference, variance inflation factor (VIF) tests were conducted to rationally eliminate and adjust the preliminary selected indicators, ensuring that the selected indicators have high independence and explanatory power. Ultimately, 14 influencing factors across the three categories were identified (see Table 1), laying a solid foundation for the subsequent model analysis.

Table 1 Indicator System for Influencing Factors and Their Statistical Characteristics

Category	Description	Mean	Standard Deviation	VIF
Functional Attributes	Proportion of commercial/service land	0.162	0.182	3.45
	Proportion of residential land	0.220	0.228	2.98
	Proportion of blue-green space	0.075	0.117	1.12
	Proportion of industrial/logistics land	0.101	0.190	3.87
	Land use mix index	1.218	0.390	4.23
	Land use evenness index	0.708	0.256	3.71
Spatial Form	Average building shape coefficient	0.0155	0.009	2.35
	Average building aspect ratio	2.899	1.237	2.79
	Building density	0.133	0.100	4.15
	Average number of floors	8.598	5.001	3.56
	Floor Area Ratio (FAR)	1.462	1.333	4.87
Carrying Capacity	Population density	97.601	71.651	3.62
	POI Density	557.414	778.443	3.99
	Road network density	0.016	0.009	2.74

2.3 Model Introduction

This study employs two spatial statistical models: Multi-scale Geographically Weighted Regression (MGWR) and Geo-Detector. The aim is to reveal the spatial heterogeneity and multi-factor interaction mechanisms affecting the carbon emission intensity of urban land use.

2.3.1 Multi-scale Geographically Weighted Regression (MGWR)

The MGWR model is an extension of the Geographically Weighted Regression (GWR) model. The difference is that MGWR allows the effect scale of different explanatory variables to vary spatially. By setting a bandwidth parameter for each variable individually, MGWR captures the strength of the effect of each variable on the dependent variable within different spatial ranges. Compared to traditional GWR, which uses a unified bandwidth, MGWR better reflects the diversity of spatial scales of driving factors in complex urban environments, and reveals the differences in the effects of various factors at local and macro scales. This helps identify the carbon reduction potential differences in land use functions, spatial forms, and carrying capacity across regions, improving the model's fitting effect and explanatory power (Laffan and Bickford, 2005).

$$y_i = \beta_0(u_i, v_i) + \sum_{k=1}^{r} \beta_k(bw_k, u_i, v_i)x_{ik} + \varepsilon_i$$

Where y_i represents the carbon emission intensity of the i-th geographic unit, x_{ik} represents the k-th influencing factor for the i-th unit, β_k is the regression coefficient with a location-dependent bandwidth, and ε_i is the error term. MGWR minimizes local weighted squared errors to estimate the spatial heterogeneity coefficients of each variable, achieving precise characterization of the spatial scale of the influence of different factors.

2.3.2 Geo-Detector

Geo-Detector is a factor influence evaluation tool based on spatial statistics, used to measure the degree of consistency between the spatial distributions of explanatory variables and the dependent variable. The core idea is that if an influencing factor shows a high spatial consistency with carbon emission intensity, it has a strong explanatory power for carbon emissions.

Geo-Detector reflects the proportion of variance in the spatial variation of carbon emissions explained by a factor by calculating a statistical value, as defined below:

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

Where N is the total sample size, σ^2 is the total variance of carbon emission intensity, N_h and σ_h^2 are the sample size and variance within the h-th subdivision, and L represents the number of subdivisions. The value of q ranges from [0, 1], with a value closer to 1 indicating stronger explanatory power.

Furthermore, Geo-Detector is used for factor interaction analysis. By comparing the combined value of factor interactions with the value of individual factors, it identifies complex interaction patterns such as factor combination enhancement and nonlinear enhancement, revealing the pathways through which multiple factors synergistically affect carbon emissions.

3. Analysis of Spatial Distribution Characteristics and Driving Mechanisms of Carbon Emissions in Nanjing's Main Urban Area

3.1 Spatial Distribution Characteristics of Carbon Emissions

Based on the ODIAC global carbon emission data with a 1-kilometer resolution, combined with the administrative boundaries and land use information of Nanjing's main urban area, this study mapped the spatial distribution of carbon emission intensity in 2023 (see Figure 2). Overall, the carbon emission intensity in Nanjing's main urban area shows significant spatial heterogeneity, with high carbon emission zones concentrated primarily in the urban core and near major transportation hubs.

Specifically, the areas with the highest carbon emission intensity are located to the west of the Xinjiekou commercial district and around Nanjing South Railway Station. These regions have frequent economic activities, high commercial density, and significant population and traffic flow, leading to higher energy consumption and carbon emission levels. High carbon emission units exhibit a clear "core-periphery" gradient structure, with emission intensity gradually decreasing as the distance from the core increases, forming a concentric "layered" distribution pattern. The carbon emissions in the urban periphery, as well as in water bodies and green spaces, are significantly lower. This distribution pattern reflects the dominant role of the urban core as a hub for economic and social activities, contributing substantially to carbon emissions.

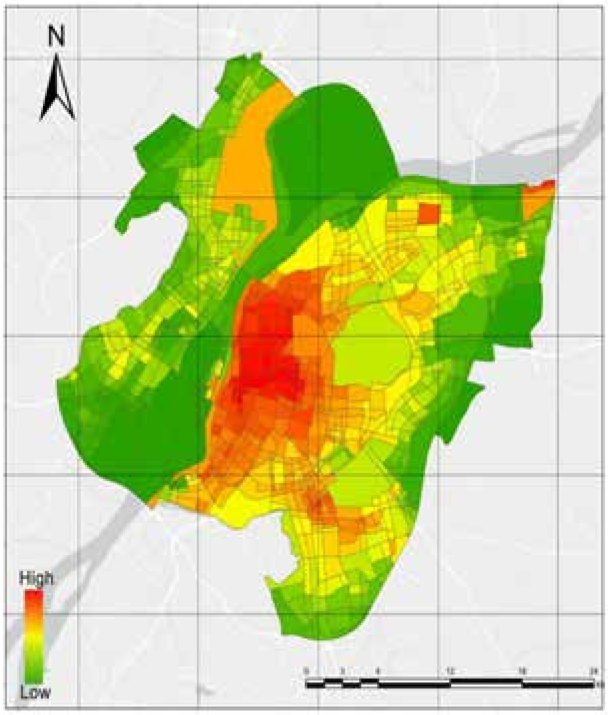


Figure 2 Spatial Distribution Map of Carbon Emission Intensity in 2023

3.2 Driving Mechanism Analysis of Carbon Emissions Based on Multi-scale Geographically Weighted Regression (MGWR)

3.2.1 Performance Comparison

To further analyze the driving mechanisms of carbon emissions in Nanjing's main urban area, this study uses the Multi-scale Geographically Weighted Regression (MGWR) model. Compared to the traditional Geographically Weighted Regression (GWR), the MGWR model is more flexible in capturing spatial heterogeneity and local variations in driving factors by selecting adaptive bandwidths (Omrani et al., 2025). This model can accurately reflect the differences in driving factors across different regions, thereby improving the model's explanatory power and prediction accuracy.

In terms of model performance comparison, we compared the Ordinary Least Squares (OLS), Geographically Weighted Regression (GWR), and Multi-scale Geographically Weighted Regression (MGWR) models. According to the results in Table 2, the MGWR model outperforms both OLS and GWR in all performance metrics. Specifically, the R-squared for MGWR is 0.7386, and the adjusted R-squared (Adj R-squared) is 0.7126, both significantly higher than those of OLS and GWR, indicating stronger fitting capabilities. This suggests that MGWR can better explain the variation in carbon emission intensity. Therefore, MGWR was chosen as the primary model for analyzing the driving mechanisms of carbon emissions in this study.

Table 2 Comparison of Model Fitting Performance

Parameter	Ordinary Least Squares (OLS)	Geographically Weighted Regression (GWR)	Multi-scale Geographically Weighted Regression (MGWR)
R-squared	0.5062	0.6748	0.7386
Adj R-squared	0.4984	0.6028	0.7126
σ^2	0.70862	0.3971	0.2874
AICc	1959.714	1856.1724	1536.6730

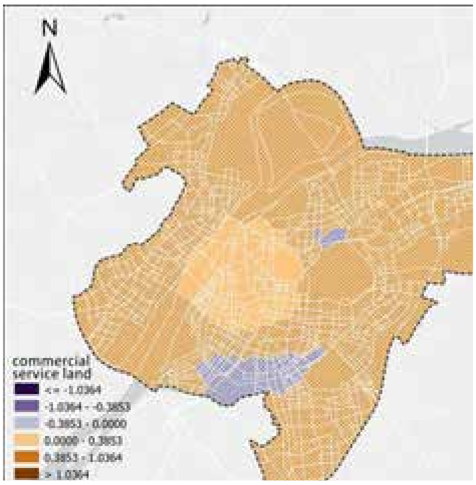
3.2.2 MGWR Results Analysis

(1) Functional Attribute Factors

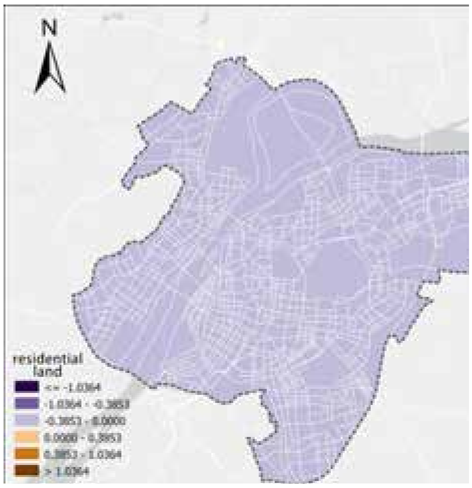
Firstly, the effects of the proportion of commercial and public service land (Figure 3a) and industrial and logistics land (Figure 3d) on carbon emission intensity exhibit significant spatial heterogeneity within the main urban area. The carbon emission intensity of commercial land generally shows a positive correlation, particularly in high-density urban core areas. As the proportion of commercial land increases, the carbon emission intensity also rises (You et al., 2023). Similarly, the effect of industrial and logistics land on carbon emission intensity is positive in most areas, especially in the urban periphery, where the expansion of industrial land tends to bring higher carbon emission levels. However, in certain specific areas of Nanjing, such as the Zhongshan Scenic Area and the southern part of the city, the increase in industrial land did not significantly raise the carbon emission intensity. On the contrary, it exhibited a weak negative correlation.

In contrast, the proportion of residential land (Figure 3b), blue-green space (Figure 3c), land use mix index (Figure 3e), and land use evenness index (Figure 3f) generally show a negative relationship with carbon emission intensity, and their influence mechanisms within the main urban area are consistent, with no significant spatial heterogeneity. Areas with a high proportion of residential land typically have lower carbon emission intensity, which is related to the fact that residential land is primarily used for daily living and has lower energy consumption (Cai et al., 2025), especially when compared to commercial and industrial land. The increase in blue-green space helps enhance the ecological function of the urban environment, thereby reducing carbon emission intensity. Blue-green spaces not only reduce carbon dioxide emissions by increasing carbon sequestration effects but also improve the microclimate and reduce the urban heat island effect, further decreasing energy consumption and carbon emissions. Both the land use mix index and the land use evenness index also show a negative relationship. Previous studies, from the perspective of urban agglomerations, have demonstrated that the rational layout of multifunctional land uses within a plot can effectively reduce carbon emission intensity (Kang et al., 2023). A high land use mix not only helps reduce long-distance travel and traffic congestion but also improves carbon emission outcomes through the introduction of ecological spaces such as parks and green spaces.

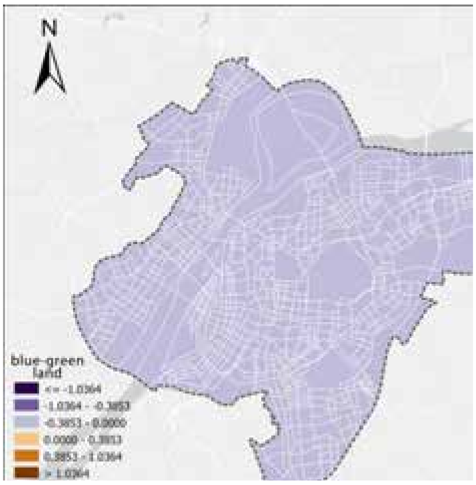
ΔaΔProportion of commercial/service land



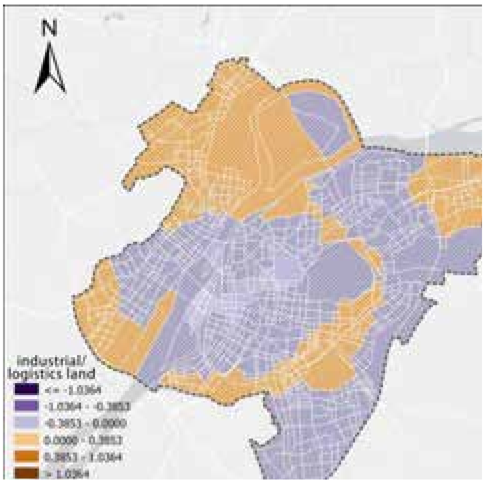
(b) Proportion of residential land



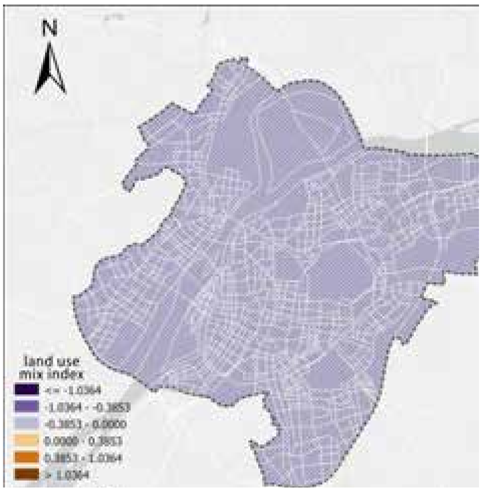
(c) Proportion of blue-green space



(d) Proportion of industrial/logistics land



(e) Land use mix index



(f) Land use evenness index

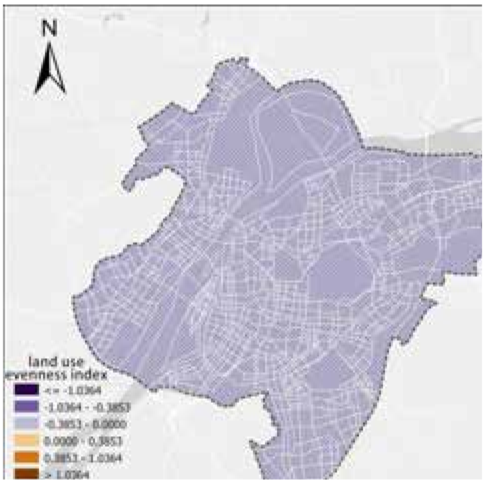


Figure 3 Analysis Results of Functional Attribute Factors

(2) Spatial Form Factor

The average building shape coefficient and average building aspect ratio are important indicators that reflect the extent of building exposure to the external environment. As shown in Figure 4a, the building shape coefficient has a positive global correlation with carbon emission intensity, meaning that as the building shape coefficient increases, the building's contact area with the environment increases, leading to higher energy consumption and, consequently, higher carbon emission intensity. In contrast, the relationship between the building aspect ratio and carbon emission intensity is more complex (Figure 4b). Higher building aspect ratios are generally associated with higher carbon emission intensity, but in areas like Bagua Island, Shuanglong Avenue, Qixia Avenue, and Wuhua Road in Nanjing, a higher building aspect ratio does not significantly increase carbon emission intensity. This may be related to local climatic conditions, building energy efficiency, and the characteristics of the surrounding environment, with microclimate effects potentially having a varying impact on the carbon emission mechanism (Dong et al., 2023).

On the other hand, the relationship between building density and carbon emission intensity shows significant spatial heterogeneity across different regions (Figure 4c). In the Xianlin area of Nanjing, building density is positively correlated with carbon emission intensity, whereas in other areas of the main urban area, building density shows a negative correlation with carbon emission intensity. This suggests that in some areas, a moderate increase in building density helps reduce carbon emission intensity. This is consistent with findings from some urban studies. For example, research in Shanghai has shown that after a certain level of floor area ratio is reached, increasing building density reduces carbon emissions, especially when land use efficiency is improved and urban sprawl is reduced, leading to decreased traffic-related emissions (Tian et al., 2024b, Sun and Song, 2024). Finally, the average number of floors in buildings is positively correlated with carbon emission intensity across all study units in the main urban area (Figure 4d). From a land use perspective, a higher average number of floors per unit area typically indicates a higher concentration of residential and commercial activities, leading to greater carbon emissions per unit area of land.

(a) Average building shape coefficient | (b) Average building aspect ratio

(c) Building density | (d) Average number of floors

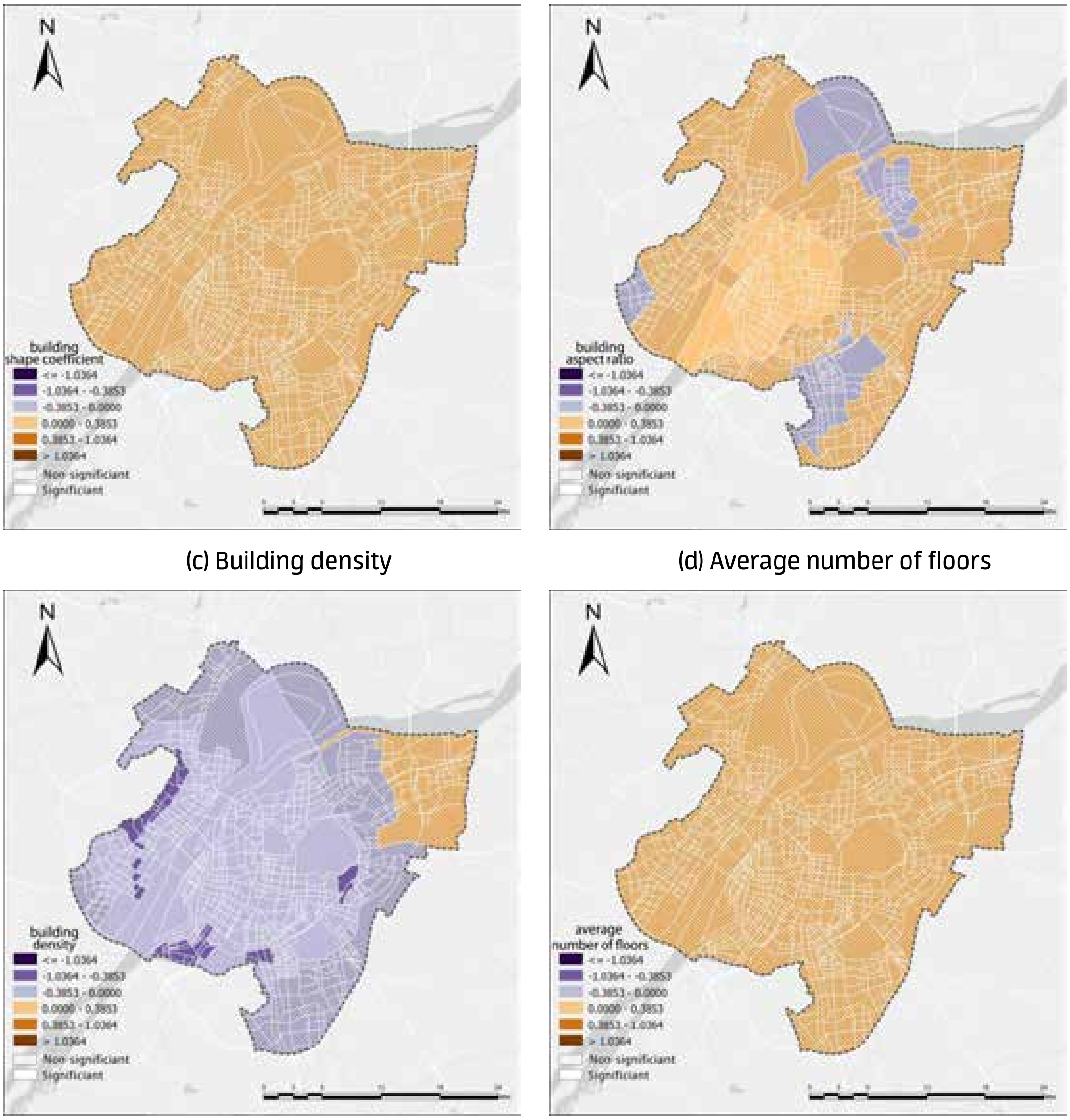


Figure 4 Analysis Results of Spatial Form Factors

(3) Carrying Capacity Factors
Figure 5a shows that floor area ratio (FAR) is positively correlated with carbon emission intensity globally, and most regions show high statistical significance. FAR reflects the total building volume per unit land area, meaning that the higher the FAR, the larger the building area, and the higher the energy consumption and carbon emissions. The regression results for population density in Figure 5b show significant spatial heterogeneity. In the central area of the main urban area, population density is positively correlated with carbon emission intensity, indicating that an increase in population density leads to higher energy consumption and carbon emissions. However, in some peripheral areas of the city, population density shows a negative correlation with carbon emission intensity.

Similarly, the relationship between POI density and carbon emission intensity also exhibits spatial differences (Figure 5c). In the city center, POI density is positively correlated with carbon emission intensity, suggesting that more commercial facilities, service locations, and employment opportunities attract large amounts of human and logistical traffic, thus increasing carbon emissions from land use.

However, in some areas to the west of the Yangtze River, POI density shows a negative correlation with carbon emission intensity, indicating that areas with high POI density might promote more green travel and consumption patterns, thus reducing carbon emission intensity.

Finally, Figure 5d shows that road network density is positively correlated with carbon emission intensity across all study units in the main urban area. Although some studies suggest that high road network density helps reduce traffic congestion and encourages green travel at large scales, in the context of urban land use in this study, a dense road network often leads to higher traffic volumes, which in turn increases traffic-related carbon emissions. This indicates that the impact mechanism of road network density is scale-dependent, and different conclusions may be drawn at different scales.

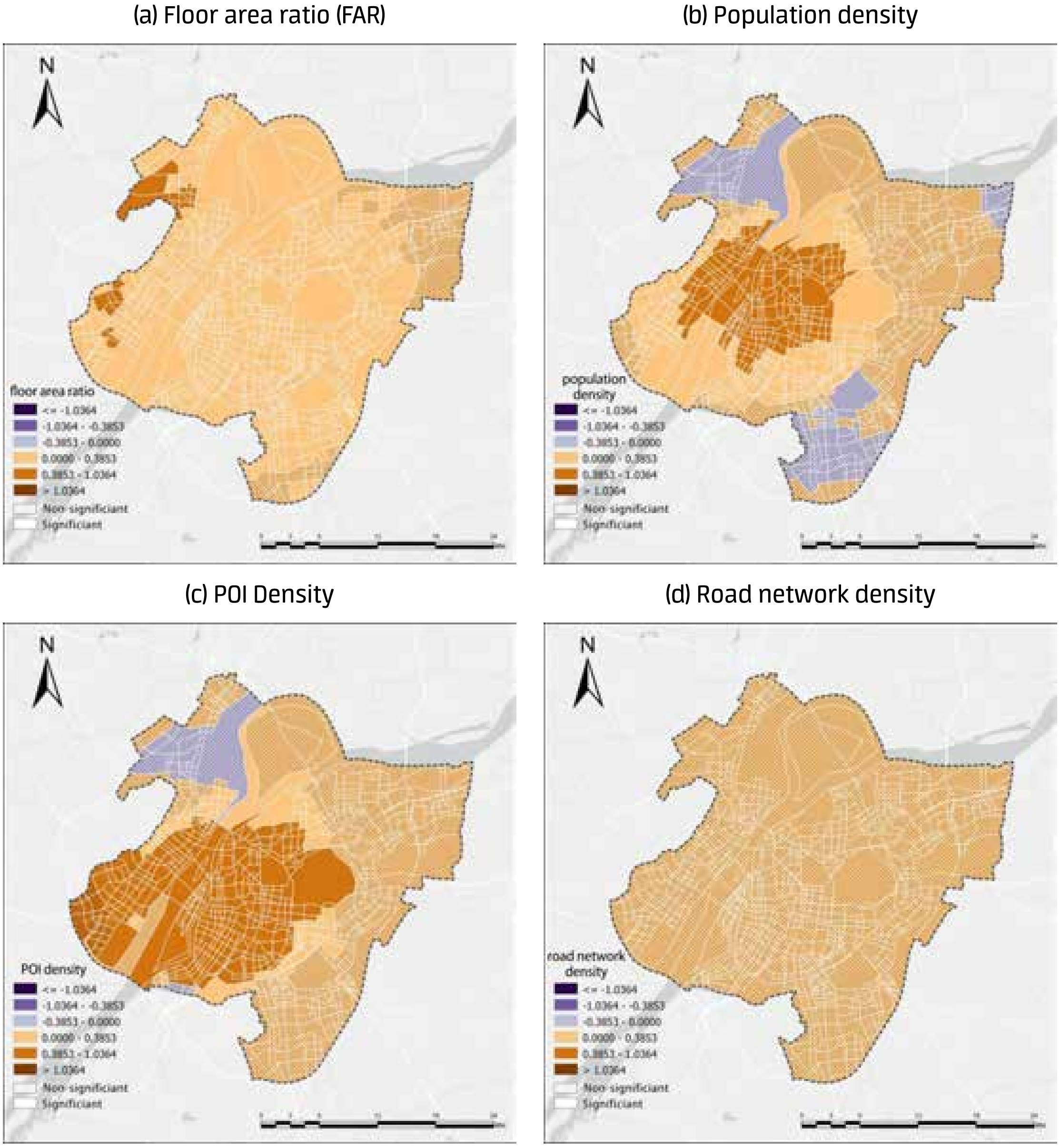


Figure 5 Analysis Results of Carrying Capacity Factors

3.3 Analysis of Factor Interaction Mechanisms Based on Geo-Detector

3.3.1 Analysis of Results from Factor Geo-Detector

This study analyzed the influencing factors of urban land carbon emissions and their explanatory power using Geo-Detector. Geo-Detector provides the explanatory weight (q value) and statistical significance (P value) of each factor, which are used to assess the contribution of these factors to the spatial distribution of carbon emissions. According to the results (see Table 3), all influencing factors, except for the uniformity index (X6, P value = 0.078), show significant correlations with carbon emission intensity, with P values all less than 0.001. This indicates that most factors can well explain the spatial distribution pattern of carbon emission intensity.

From the q values, it is evident that the carrying capacity factors contribute the most to the spatial variation of carbon emissions. The carrying capacity factors include floor area ratio (FAR), population density, POI density, and road network density. These factors directly reflect the economic, population, traffic, and building load attributes of land units. For example, the q value for population density is 0.407, which means population density can explain 40% of the spatial heterogeneity in carbon emission intensity, making it the most influential factor. The q values for FAR and POI density are 0.340 and 0.343, respectively, indicating that they also play important roles in explaining the spatial distribution of carbon emission intensity. In contrast, the spatial form and functional attribute factors have weaker explanatory power, with generally lower q values.

Table 3: Single-Factor Geo-Detector Analysis Results

Influencing Factor	**X1**	**X2**	**X3**	**X4**	**X5**	**X6**	**X7**
q value	0.119	0.068	0.084	0.028	0.036	0.009	0.054
P value	0.000	0.000	0.000	0.000	0.000	0.078	0.000
Influencing Factor	**X8**	**X9**	**X10**	**X11**	**X12**	**X13**	**X14**
q value	0.024	0.162	0.113	0.340	0.407	0.343	0.115
P value	0.000	0.000	0.000	0.000	0.000	0.000	0.000

3.3.2 Analysis of Results from Interaction Geo-Detector

Geo-Detector not only analyzes the contribution of individual factors to carbon emission intensity but also explores the interactions between these factors. The interaction Geo-Detector results in Figure 6 show that there are significant interactions between factors, and these interactions generally provide a higher explanatory power for carbon emission intensity than the individual factors alone. In particular, the interaction between population density and POI density has a q value of 0.548, indicating that the combined effect of these two factors can better explain the spatial variation of carbon emission intensity. This result further confirms that population and economic activities are the main sources of carbon emissions in cities, and their interaction amplifies their impact on carbon emissions.

Furthermore, single factors such as the proportion of commercial and public service land, residential land, and industrial and logistics land, when combined with carrying capacity factors (e.g., FAR), show significantly improved explanatory power. For example, the combination of the proportion of commercial and public service land with FAR increases its explanatory power for carbon emissions to 44.87%, while the interaction of industrial and logistics land with FAR explains 36.09% of the carbon emission intensity. These results are much higher than the explanatory power of the factors before the interaction (e.g., the proportion of commercial land at 11.9% and industrial land at 6.84%). This suggests that the influence of functional attribute factors on carbon emissions is not independent but is closely intertwined with factors such as population, economy, and transportation, and thus requires a comprehensive consideration of interactions between these factors.

Overall, among the 91 interaction influence indicators analyzed by the interaction Geo-Detector, 37 show a two-factor enhancement pattern, while the remaining 54 exhibit a non-linear enhancement pattern, accounting for more than 60%. This phenomenon indicates that the spatial distribution of land carbon emission intensity is the result of multiple factors acting together, and the formulation of carbon reduction strategies should consider the combined effects of various factors, rather than the influence of any single factor.

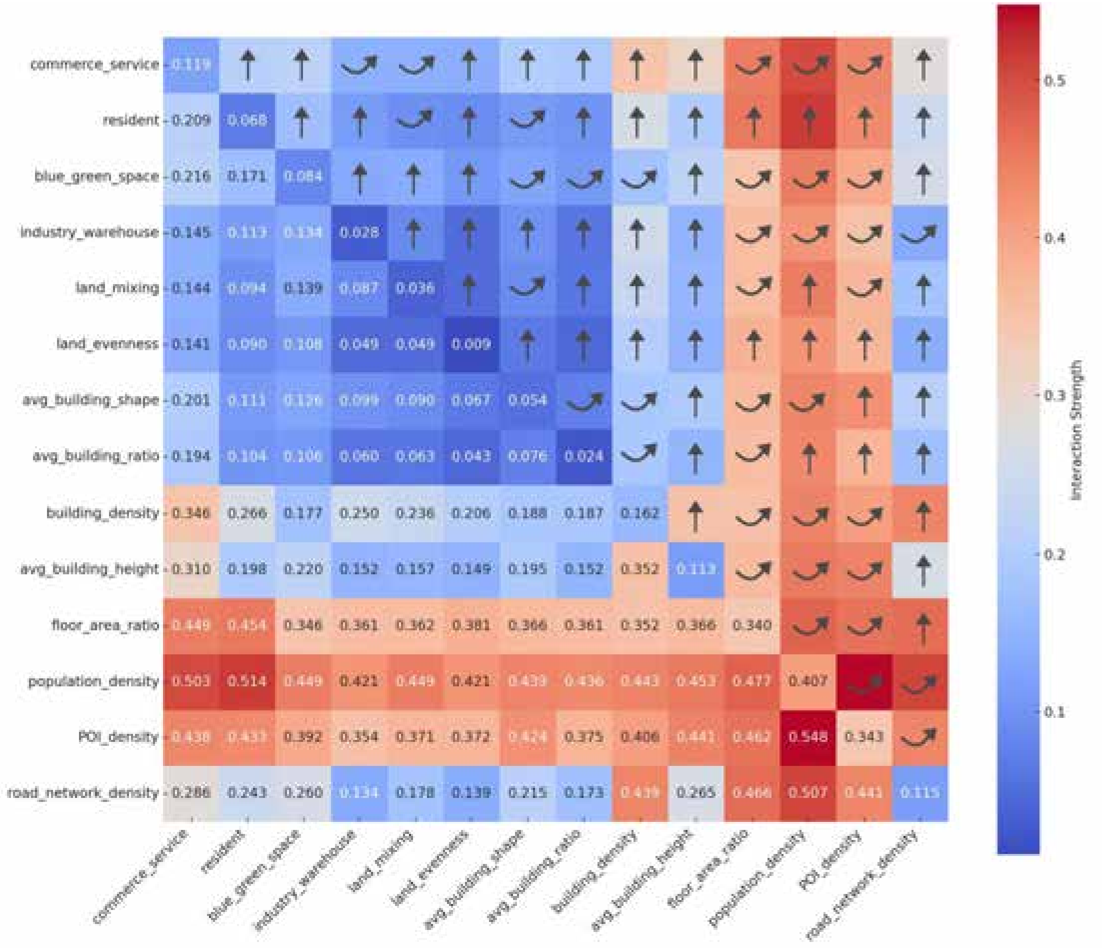


Figure 6 Two-Factor Interaction Strength Detection Results

4. Spatial Micro-Update Scheme Practice under Low-Carbon Guidance

4.1 Site Introduction

The plot selected for the micro-update design in this study is located in the northern part of the study area, within the Liuhe District of Nanjing. The existing buildings on the site are relatively old, with some facades in urgent need of repair. Additionally, there are no sizable green spaces or parks within the site, and public spaces are lacking, indicating a clear demand for urban renewal.

The current situation of the site is illustrated in Figure 7. The land use within the site is primarily residential land , with three commercial areas and some mixed-use commercial and residential land. Except for the high-rise residential area located on the northern side of the site, the remaining residential areas are low-rise (4-6 floors). Additionally, there are sanitation and gas facilities within the site. On the eastern side of the financial and insurance land, there is a section of abandoned railway land, which has lost its practical value. From a land use floor area ratio perspective, except for the high-rise residential area on the northern side (with a floor area ratio of 3.5), the floor area ratio of the remaining land is below 1.6.

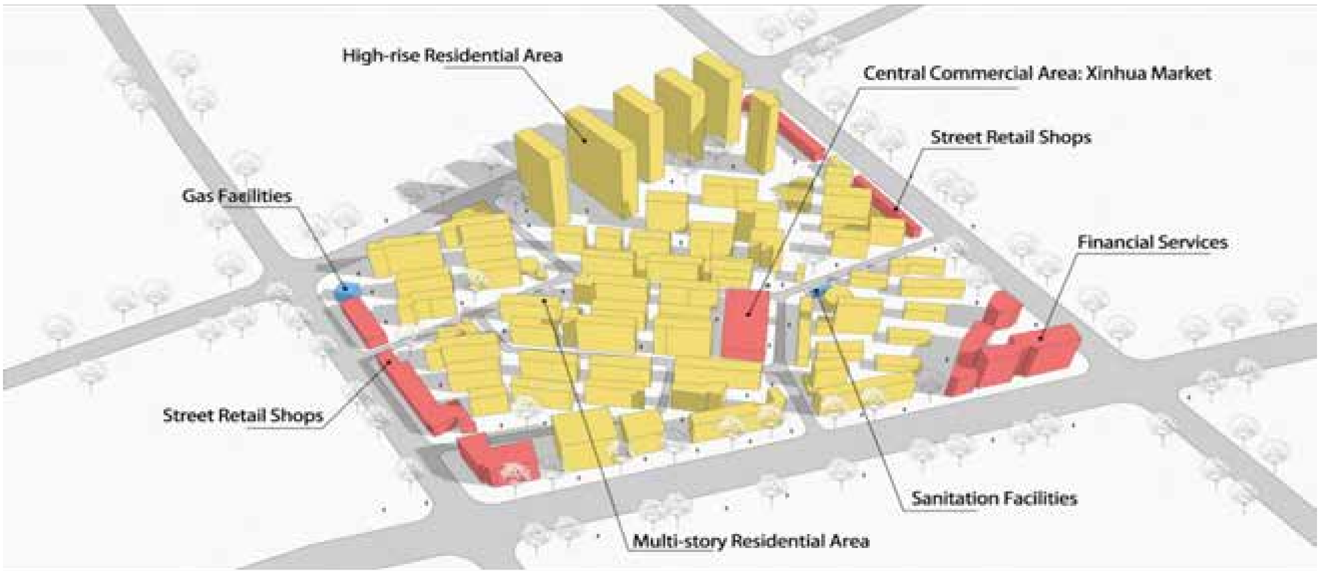


Figure 7 Current Site Situation Diagram

4.2 Micro-Update Scheme

The micro-update scheme proposed in this study focuses on fine-tuning the functional attributes and building forms of urban land plots to achieve a dual enhancement of both low-carbon benefits and environmental quality. Based on the local analysis results of the multi-scale geographically weighted regression model, of the fourteen influencing factors, the proportion of residential land, blue-green space proportion, land use evenness, land use mix, and building density have a negative impact on carbon emission intensity, while the remaining factors show a positive impact. Therefore, the core objective of this scheme is to optimize land use structure and building form, reduce the impact of positive factors, and enhance the negative factors. This will allow for a reduction in carbon emissions and an improvement in environmental quality while maintaining the overall development intensity of the plot.

(1) Fine-Tuning of Land Use Attributes

According to the regression model analysis, carbon emission intensity shows a negative correlation with land use mix, land use evenness, blue-green space proportion, and residential land proportion, and a positive correlation with industrial/logistics land proportion and commercial/public service facilities land proportion. Based on the current situation of the plot and the regression analysis results, the land use attribute adjustments in this scheme mainly include the following aspects:

- Reduce the residential land in the central part of the site from 1.7 hectares to 1.4 hectares. To maintain the land's carrying capacity, the floor area ratio (FAR) of the reduced 1.4-hectare area will be increased from 1.6 to 2.0, ensuring improved land use efficiency.
- Convert the vacated 0.4-hectare residential land into park green space, creating a centralized public space to meet the daily recreational needs of the community (Sun, 2024).
- Transform the abandoned railway land (0.34 hectares) on the eastern side of the site into park green space, constructing a linear park for residents' daily use, providing more green open space.

These fine-tuning measures not only enhance the land use mix and land use evenness but also effectively increase the blue-green space proportion from 0% to 5.05%. While providing public space, these adjustments contribute to a reduction in carbon emission intensity.

(2) Fine-Tuning of Spatial Form

In terms of spatial form adjustments, this scheme maintains the overall spatial structure of the plot while achieving low-carbon effects through localized optimization of building forms. The specific adjustment measures include:

- Break up the long continuous building facades around the site by arranging buildings in a more reasonable layout, thereby reducing the building's aspect ratio and external surface area, which in turn lowers building energy consumption.
- Utilize the existing spatial resources of the site to introduce pocket parks in appropriate locations, providing more green open space for residents.
- Based on the adjusted central park green space and the linear park on the eastern side, design a slow-traffic system running through the site and connect it effectively to the pocket parks, creating a pedestrian-friendly low-carbon commuting environment.
- Implement rooftop greening on some buildings where feasible, increasing green space to further reduce building energy consumption.
- Rebuild buildings that were demolished to make way for park green spaces after adjusting the FAR, to maintain the stability of the total population in the area and avoid socio-economic instability caused by demolition.

These spatial form adjustments make full use of the existing resources within the site, not only optimizing the building layout and improving the quality of public spaces but also creating a suitable walking environment that reduces carbon emissions from transportation. The specific spatial transformation plan is shown in Figure 8.

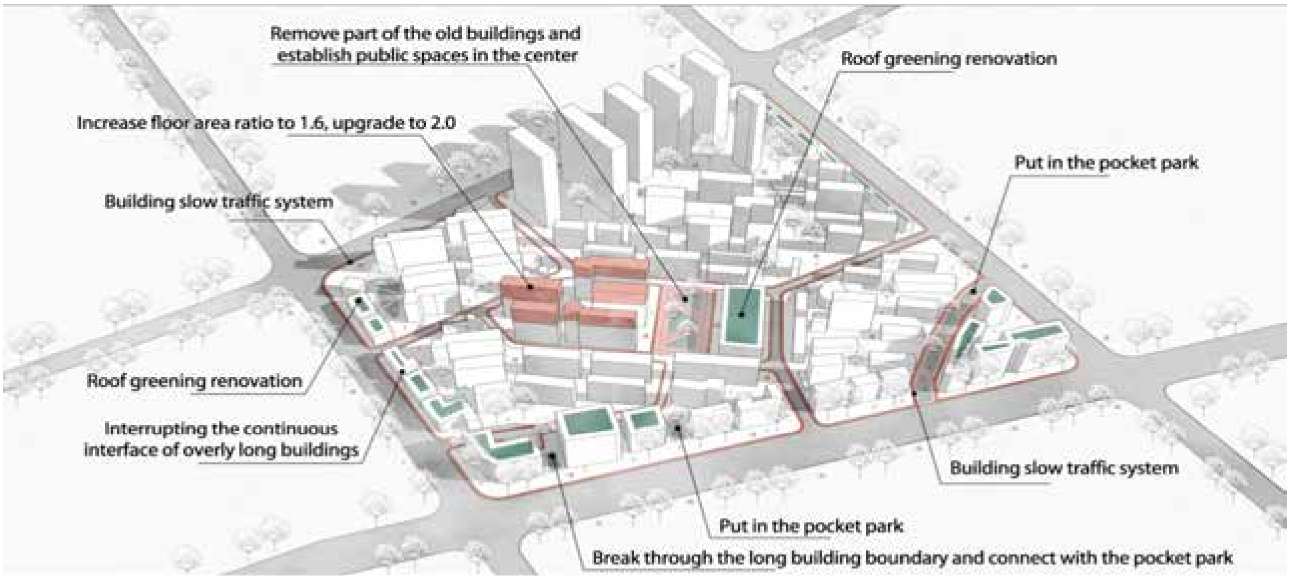


Figure 8 Adjusted Site Situation Diagram

4.3 Low-Carbon Performance Evaluation of the Micro-Update Scheme

The micro-update scheme proposed in this study includes changes in land use type and localized building spatial adjustments, aiming to reduce carbon emissions by optimizing land use and building form. Traditional low-carbon space design studies often focus on qualitative analysis, making it difficult to quantitatively assess the carbon emission performance before and after the design scheme. This study extracts the local regression equations from the multi-scale geographically weighted model for the plot, standardizes the updated influencing factors, and inputs them into the regression model to calculate the carbon emission intensity of the updated plot. This is then compared with the pre-update carbon emission intensity to quantitatively evaluate the low-carbon performance of the micro-update scheme.

According to the comparison results shown in Table 4, the update scheme mainly includes the transformation of residential land into park green space, adjustments in building density, and optimization of floor area ratio (FAR) and land use type. In terms of functional attributes, the proportion of residential land decreased from 70.7% to 68.0%, while the proportion of blue-green space increased from 0% to 5.1%. This change improved the land use mix and evenness, with values rising from 0.801 and 0.499 to 0.947 and 0.590, respectively.

Additionally, the floor area ratio slightly increased from 2.514 to 2.519, but considering the other adjustments, this change contributed little to the reduction in carbon emission intensity.

In terms of spatial form, the building shape coefficient increased from 0.311 to 0.315, indicating a slight increase in the contact area between buildings and the environment, although the change is minimal. The building aspect ratio decreased from 3.624 to 3.207, showing that adjustments to street-facing buildings effectively reduced their external surface area and energy consumption. Building density decreased from 0.233 to 0.221, indicating that appropriately increasing building density in certain areas has a positive effect on controlling carbon emissions.

According to the results from the MGWR regression model, the annual carbon emission intensity of the updated plot is 6.38 kg/m³, which is a reduction of 0.58 kg/m³ (8.38%) compared to the pre-update intensity of 6.96 kg/m³. The total annual carbon emissions for the plot decreased from 1,827.33 tons to 1,674.20 tons, resulting in a reduction of 153 tons of carbon emissions. These results demonstrate that through the optimization of land use attributes and building form in the micro-update scheme, significant carbon emission reduction can be achieved.

Table 4 Comparison of the Micro-Update Scheme Before and After

Variable Type	Variable Name	Effect	Pre-Update	Post-Update	Change
Functional Attributes	Proportion of commercial/ service land	Positive	0.069	0.069	No change
	Proportion of residential land	Negative	0.707	0.680	Decrease
	Proportion of blue-green space	Positive	0.00	0.00	No change
	Proportion of industrial/ logistics land	Negative	0.00	0.051	Increase
	Land use mix index	Negative	0.801	0.947	Increase
	Land use evenness index	Negative	0.499	0.590	Increase
Spatial Form	Average building shape coefficient	Positive	0.311	0.315	Increase
	Average building aspect ratio	Positive	3.624	3.207	Decrease
	Building density	Negative	0.233	0.221	Decrease
	Average number of floors	Positive	10.769	11.361	Increase
Carrying Capacity	Floor area ratio (FAR)	Positive	2.514	2.519	Increase
	Population density	Positive	Assumed unchanged	Assumed unchanged	No change
	POI density	Positive	Assumed unchanged	Assumed unchanged	No change
	Road network density	Positive	0.00	0.016	Increase

5. Discussion and Conclusion

This study thoroughly investigates the spatial distribution characteristics and driving mechanisms of carbon emissions in Nanjing's main urban area. Using multi-scale Geographically Weighted Regression (MGWR) and Geo-Detector models, we analyzed various factors influencing urban land carbon emission intensity and their interactions. The results show that the impacts of functional attributes, spatial form, and carrying capacity on carbon emission intensity exhibit significant spatial heterogeneity. In particular, carrying capacity factors such as population density, floor area ratio (FAR), and POI density contribute the most to carbon emission intensity, with the highest explanatory power.

First, based on the analysis of the three major categories of influencing factors, functional attributes and spatial form factors display significant differentiation. Specifically, different sub-factors do not show uniform characteristics in their mechanisms affecting carbon emission intensity. For instance, factors such as the proportion of commercial and public service land, average number of floors, and FAR have a positive effect on carbon emission intensity in most areas of the main urban region, meaning that an increase in these factors directly leads to a rise in carbon emission intensity. From a low-carbon construction perspective, it is necessary to reasonably limit the upper limits of these factors. On the other hand, factors such as the proportion of residential land, blue-green space, and land use mix generally show a negative effect on carbon emission intensity in most areas, and increasing the proportion of these factors can effectively reduce carbon emission intensity, particularly in urban core areas (Yang, 2023, Sun, 2024).

Furthermore, carrying capacity factors (such as FAR, population density, and POI density) have the highest explanatory power for carbon emission intensity, with the q value for population density being 0.407, indicating the greatest contribution to spatial heterogeneity in carbon emissions. Studies have shown that carrying capacity factors directly reflect the economic, population, traffic, and building load attributes of land units, and are positively correlated with carbon emission intensity (Ming et al., 2024). Based on this, when implementing the micro-update scheme, it is necessary to make targeted adjustments according to the carrying capacity of specific regions.

From the perspective of factor interactions, 60% of the influencing factors show significant synergistic effects, indicating that the spatial distribution of carbon emission intensity in urban land is not determined by a single factor but is the result of multiple interwoven factors. In particular, the interaction between population density and POI density, with a q value of 0.548, shows that their combined effect can better explain the spatial variation of carbon emission intensity. This result further confirms the primary contribution of population and economic activities to carbon emissions (Dong et al., 2023) and suggests that the interaction of these factors amplifies their impact on carbon emissions.

The empirical analysis of the micro-update scheme also validates the above theory. By adjusting land use attributes and optimizing spatial form, the micro-update scheme effectively reduced the carbon emission intensity of the plot. Specifically, through the adjustments in FAR, residential land, and park green space, the carbon emission intensity decreased from 6.96 kg/m³ to 6.38 kg/m³, and the total annual carbon emissions decreased by 153 tons, confirming the low-carbon effect of the micro-update strategy in practical application. Additionally, spatial form fine-tuning, such as adjustments in building form and building density, also contributed to reducing carbon emissions, particularly in the adjustments to building aspect ratio and building density, which effectively suppressed carbon emissions.

However, this study also has certain limitations. First, while the MGWR and Geo-Detector models provided a detailed analysis of the influencing factors of carbon emissions, assumptions about the changes in population density and POI density may not fully align with actual conditions. Future research could more precisely simulate the dynamic changes of these factors. Second, although the micro-update scheme has achieved significant reductions in carbon emissions, its comprehensive impact on urban socio-economic benefits, residents' quality of life, and urban sustainability has not been fully explored. Future studies should consider conducting comprehensive evaluations on a broader scale, especially considering the dual context of urban development and residents' needs.

Overall, this study provides a practical basis for low-carbon city construction through the quantitative analysis of the micro-update scheme's low-carbon performance. It demonstrates that optimizing land use attributes, building form, and carrying capacity can effectively reduce carbon emission intensity. The implementation of the micro-update scheme not only improves the environmental quality of the plot but also provides strong support for the realization of low-carbon cities. As low-carbon city construction goals are gradually advanced, the application of the micro-update scheme holds great potential in the renewal of small and medium-sized cities and existing urban blocks. Future work will further explore the comprehensive social, economic, and environmental impacts of the micro-update scheme to ensure the thoroughness and sustainability of low-carbon transformation.

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