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ARTICLE

Spatial Heterogeneity in the Impact of Urban Land Use on Road Traffic Carbon Dioxide Emissions

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ABSTRACT

Road traffic has become one of the major sources of carbon dioxide emissions. However, there remains a lack of consensus on how urban land use influences these emissions. This study investigates the spatial distribution of municipal-level road traffic carbon dioxide emissions and their land use drivers in Japan's Kanto region. Ordinary least squares (OLS), geographically weighted regression (GWR), and multi-scale geographically weighted regression (MGWR) models are employed to analyze the impacts of residential, industrial, and commercial land use on emissions, as well as to examine spatial heterogeneity in model residuals. The results reveal a clear spatial clustering pattern, with higher emissions in central Tokyo and lower emissions in peripheral areas. The MGWR model demonstrates the best fit and shows no spatial autocorrelation in residuals, highlighting the necessity of incorporating spatial heterogeneity. The MGWR results indicate that all three land use types significantly affect emissions, but their impacts vary spatially. Residential land use has the largest and most spatially heterogeneous effect, making it the most decisive factor. The findings underscore that effective low-carbon transportation policies cannot adopt a one-size-fits-all approach but must

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be tailored to locally dominant land-use–emission relationships. This study deepens the understanding of the spatial relationship between urban land use structure and road traffic carbon emissions and provides empirical support for sustainable urban development and low-carbon transportation policies.

Keywords: Carbon Dioxide Emission; Road Traffic; Spatial Analysis; Spatial Heterogeneity; Urban Land Use

1. Introduction

Greenhouse gas (GHG) emissions are the primary driver of global climate warming, leading to increasingly frequent extreme weather events, ecological imbalances, and growing socio-economic instability. Since the adoption of the Paris Agreement in 2015, the control of greenhouse gas emissions has become a central objective of environmental policies worldwide [1]. Carbon dioxide, as the most significant greenhouse gas, accounts for more than 70% of total global emissions. Its reduction plays a crucial role in the progress toward carbon peaking and carbon neutrality targets. According to the International Energy Agency, despite the accelerated deployment of clean energy technologies in recent years, global energy-related carbon dioxide emissions still increased by 410 million t in 2023. This brought the total to a record high of 37.4 billion t, indicating that the pressure on carbon dioxide reduction remains severe [2,3].

Public data indicate that industrial production, fossil fuel-based power generation, and transportation are the three primary sources of energy-related carbon emissions. The transportation sector consistently accounts for a substantial share of carbon dioxide emissions, contributing approximately 24% of global energy-related emissions. Road transport is the largest source within the transport sector, accounting for nearly three quarters of its emissions [4,5]. As urbanization continues to progress and motor vehicle use intensifies, emissions from road traffic have shown a persistent upward trend. Therefore, it is essential to study the spatial distribution and driving mechanisms of urban road traffic carbon emissions to support sustainable urban development. These activities are highly dependent on the spatial configuration and functional distribution of land use, making it a critical subject in carbon emission research [6–10]. Previous studies show that while studies on carbon emissions from the transportation sector are abundant, specific studies focused on road traffic carbon emissions remain relatively limited.

Road traffic carbon dioxide emissions are closely related to urban land use patterns. Different types of land use have distinct impacts on travel demand, transportation mode choices, and commuting distances, which in turn influence emission levels in complex spatial ways [11–16]. Existing studies attempted to interpret these relationships through several urban theories. Compact city theory and transit-oriented development emphasize that residential concentration and proximity to high-capacity public transport can reduce commuting distances and automobile dependence, thereby lowering traffic-related emissions [17–20]. Job-housing balance theory further suggests that the spatial alignment between residential areas and employment centers plays a critical role in shaping daily travel behavior and commuting intensity [21,22]. Investigating the relationship between urban land use configuration and road traffic carbon emissions, and identifying the main influencing pathways, can enhance the accuracy of urban carbon accounting systems. It also provides important theoretical and practical support for integrating emission reduction strategies in the transportation sector with urban land use planning.

In terms of empirical research, early studies in this field primarily examined the relationship between urban built-up areas and carbon dioxide emissions. For instance, Reckien et al. calculated the correlation coefficients between built-up area and road traffic carbon dioxide emissions across 23 urban districts in Berlin, revealing a significant positive correlation between urban building coverage and emissions [23]. Similarly, Shu and Lam employed multiple regression models to investigate the relationship between urban land area and road traffic carbon emissions [24].

While such studies have provided valuable insights into the influencing factors of road traffic carbon dioxide emissions, they often overlook the spatial variations inherent in urban systems, which can lead to biased or incomplete conclusions. Therefore, recent studies have shifted attention to the spatial distribution characteristics of road traffic carbon emissions. Consistent with expectations, various studies have confirmed the presence of pronounced spatial heterogeneity in road traffic carbon dioxide emissions [25–28]. This observation implies that conventional models based on the assumption of spatial stationarity may be inadequate for analyzing road traffic emissions, highlighting the need for spatially sensitive analytical approaches that can more accurately capture underlying distribution patterns and driving mechanisms. In this context, the Geographically Weighted Regression (GWR) model has gained increasing traction. By incorporating a kernel function to assign spatial weights to different geographic locations, GWR enables local estimation of regression parameters and effectively captures spatially varying relationships. With the growing interest in spatial heterogeneity, several studies have adopted GWR and its extended forms. For instance, Zhou et al. developed a multi-scale GWR model using carbon emission data derived from traffic trajectories to explore the spatial effects of built environment factors on road traffic emissions [25]. Liu et al., on the other hand, applied a Geo-CNN weighted regression model to examine the nonlinear driving effects of urban built-up areas on road traffic carbon emissions [29].

However, there remains a lack of consensus on how urban land use influences road traffic carbon dioxide emissions. Specifically, existing studies report mixed conclusions regarding the emission impacts of different land-use types. Some studies suggest that compact residential development and higher land-use intensity can reduce travel distances and thus lower traffic-related carbon emissions, while others find that residential expansion, particularly in suburban contexts, is associated with increased automobile dependence and higher emissions. Similarly, commercial and industrial land uses have been found to exert both positive and weak effects on traffic emissions, depending on urban context, development stage, and transport infrastructure conditions. These contrasting findings indicate that the land-use–emission relationship is highly context-dependent, and that analyses assuming spatially uniform effects may obscure important local variations.

This study investigates the spatially varying impact of urban land use on road traffic carbon dioxide emissions in the Kanto region of Japan, which includes Tokyo and six surrounding prefectures. The research begins by assessing the spatial distribution and clustering of emissions using Moran's I. It then employs OLS, GWR, and MGWR models to examine how residential, industrial, and commercial land use affects road traffic emissions across space. By comparing the performance and results of these models, the study systematically reveals the spatial heterogeneity in the land use emissions relationship, offering localized insights that cannot be captured through global models alone. The findings aim to inform spatially differentiated policy interventions that address the environmental impacts of urban land development and transportation planning in complex metropolitan settings.

Subsequent sections of this paper are organized as follows: The second section provides the methodology covering the study area, data collection, relevant theories, and methods. Section 3 presents the results and analysis. In the fourth section, we discussed the research findings considering the previous study. In the final section, Section 5, the main findings of this study are summarized, and some effective policy recommendations are provided.

2. Materials and Methods

2.1. Study Area

This study selected the Kanto region of Japan, which comprises a total of 307 municipalities, including cities, towns, and villages within Tokyo Metropolitan (excluding its outlying islands), as well as Kanagawa, Saitama, Chiba, Ibaraki, Tochigi, and Gunma Prefectures (See **Figure 1**). As one of the most representative metropolitan areas in Japan, the Kanto region serves not only as the political, economic, and cultural center of the country, but also as the most population density and highest intensity of transportation activities. The study area covers the highly urbanized area of Tokyo to the increasingly suburbanized peripheral cities, exhibiting significant spatial heterogeneity. This diversity provides a favorable context for analyzing the mechanisms through which different urban land use structures influence transportation-related carbon dioxide emissions.

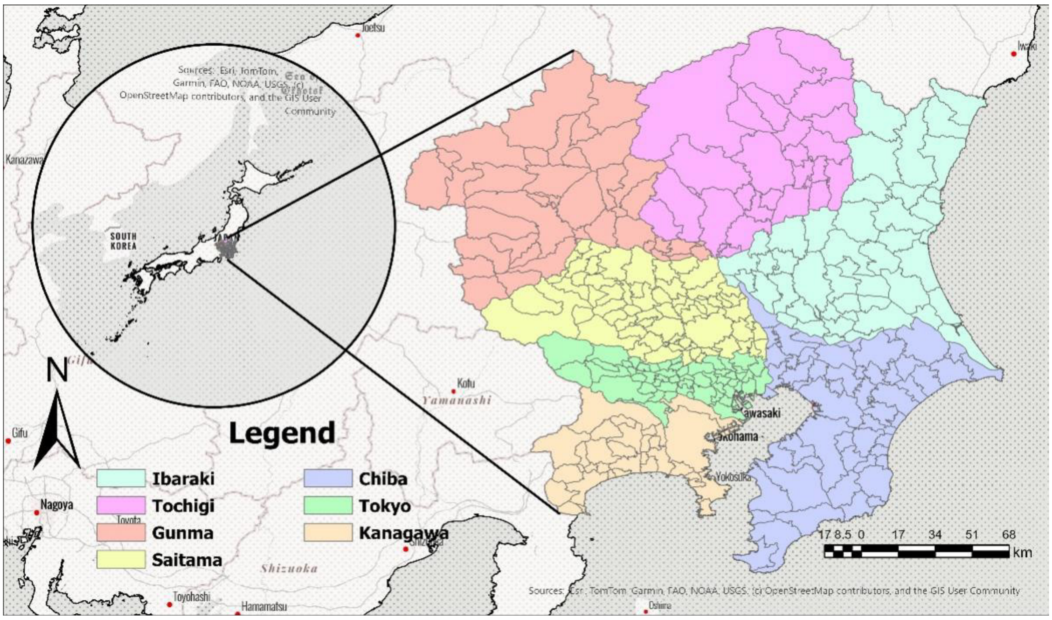


Figure 1. Study area.

2.2. Data Collection and Processing

The data used in this study, covering carbon dioxide emissions, administrative boundaries, land use, etc., were obtained from various open-source databases.

Road traffic carbon dioxide emissions were derived from the 2021 report by the Ministry of the Environment of Japan, and calculated through a proportional allocation method based on motor vehicle ownership [30]. It is worth noting that accurate vehicle kilometers traveled (VKT) or trajectory-based data are not consistently available at the municipal scale in Japan, which precludes the direct calculation of road traffic carbon dioxide emissions. Under this data constraint, vehicle ownership provides the most feasible proxy for municipal-level emission estimation. Existing empirical evidence shows a strong positive correlation between total motor vehicle stock and road traffic carbon dioxide emissions at urban and regional scales [31,32]. Moreover, within the densely populated Kanto region, intermunicipal variation in per-vehicle travel distance is relatively limited compared to variation in vehicle ownership [33]. Therefore, this approach provides a consistent and comparable basis for municipal-level spatial analysis of road traffic carbon dioxide emissions.

Per capita motor vehicle ownerships were obtained from the 2021 statistical survey conducted by the Ministry of Land, Infrastructure, Transport and Tourism of Japan. Urban road network data were collected from OpenStreetMap (OSM) using the OSMnx tool and imported into ArcGIS Pro to calculate line density, from which road network density was derived. Urban land use areas were obtained from the Urban Land Use Survey conducted by the Ministry of Land, Infrastructure, Transport and Tourism of Japan. Specific descriptions and statistics of variables are exhibited in **Table 1**, and spatial distributions are shown in **Figure 2**. It should be noted that this study focuses on urban land-use structure, measured by the areal extent of residential, industrial, and commercial land, rather than on a comprehensive characterization of urban morphology. Built-environment attributes such as population density, land-use mix, transit accessibility, and job–housing balance are therefore not included.

To avoid biased estimates caused by multicollinearity, we conducted a multicollinearity test on the explanatory variables in advance. The results show that PVN has the highest Variance Inflation Factor (VIF) value of 2.97, which is well below the commonly accepted threshold of 10 [34,35]. Therefore, it can be concluded that multicollinearity is not a concern among the explanatory variables.

Table 1. The summary of variables.

Variable	Aberration	Mean	Std.	Sample Size	Unit
Road traffic carbon dioxide emission	CE	142.180	12.156	307	kiloton
Per capita vehicle number	PVN	0.738	0.016	307	vehicle/person
Road network density	RND	16.058	0.605	307	km/km^2
Residential land area	RLA	4.200	0.373	307	km^2
Industrial land area	ILA	0.644	0.075	307	km^2
Commercial land area	CLA	0.634	0.089	307	km^2

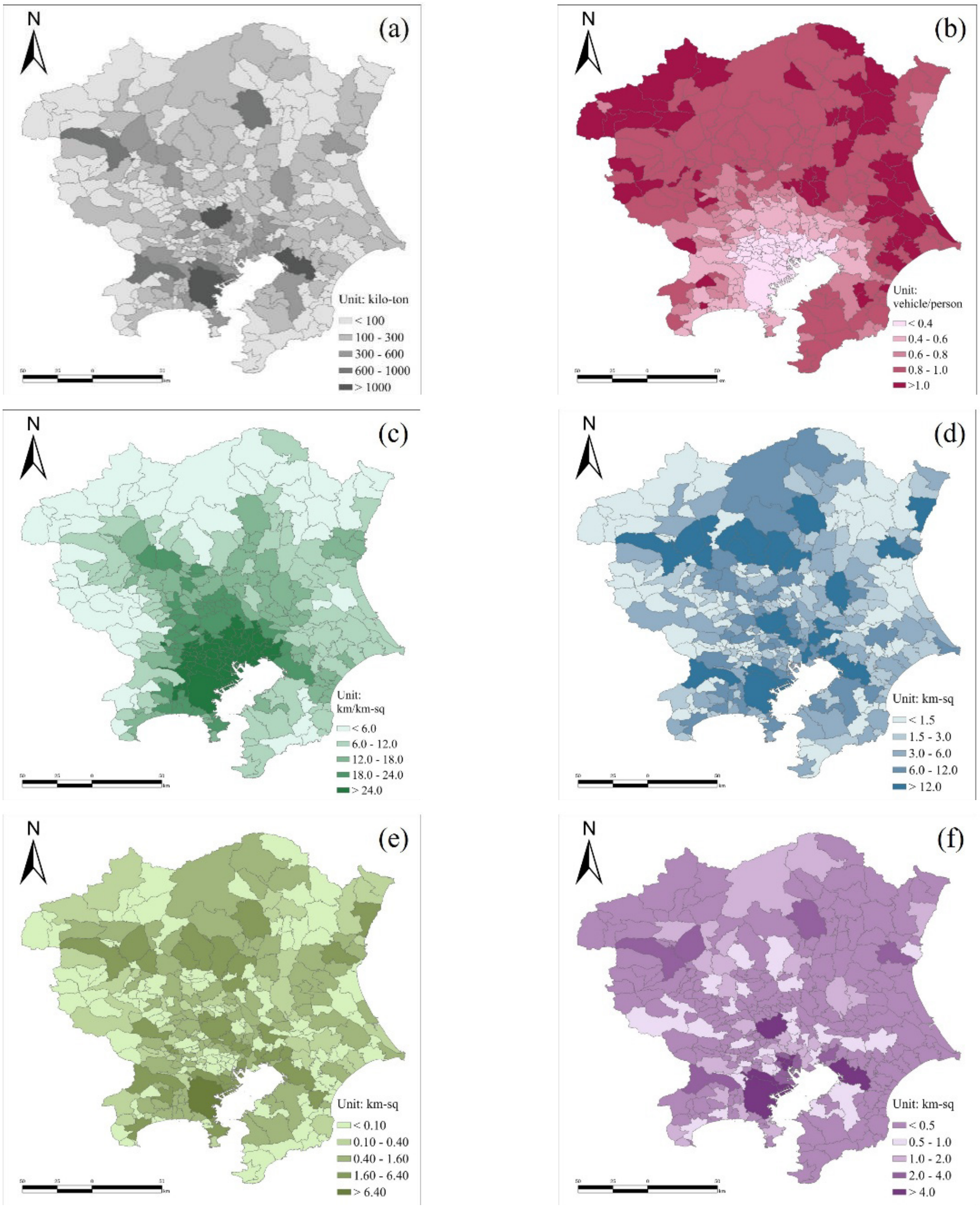


Figure 2. The spatial distribution of variables: (**a**) CE; (**b**) PVN; (**c**) RND; (**d**) RLA; (**e**) ILA; (**f**) CLA.

2.3. Spatial Autocorrelation Analysis

Generally, spatial autocorrelation analysis was performed as a preliminary step, which can not only help understand the spatial distribution characteristics but also provide a basis for subsequent model establishment. Here, Moran's I was used to measure the spatial autocorrelation of road traffic carbon dioxide emissions, and its basic form is shown in Equation (1) as follows,

$$I = \frac{n\sum_{i=1}^{n}\sum_{j=1}^{n} w_{i,j}(x_i - \bar{x})(x_j - \bar{x})}{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{i,j}(x_i - \bar{x})^2} \tag{1}$$

where, $w_{i,j}$ represents the spatial relationship between region i and geographical unit j, x_i and x_j are observations of road traffic carbon dioxide in region i and region j, and $\bar{x}$ represents the mean value of the road traffic carbon dioxide emission. Here, the spatial weight is defined according to the geographically adjacent relationship, with $w_{i,j}$ assigned the value of 1 when the region i and region j are spatially adjacent, and 0 otherwise.

The Local indicators of spatial association (LISA) cluster map based on Anselin Local Moran's I can reveal local spatial autocorrelation and help distinguish between areas with similar or divergent emission intensities relative to their neighbors. Anselin Local Moran's I can be calculated through Equation (2) as follows,

$$I_i = \frac{n(x_i - \bar{x})\sum_{i=1}^{n} w_{i,j}(x_j - \bar{x})^2}{\sum_{i=1}^{n}(x_i - \bar{x})^2} \tag{2}$$

2.4. Regression Model Establishment and Evaluation

In this study, Ordinary Least Squares Regression (OLS), Geographically Weighted Regression (GWR), and Multiscale Geographically Weighted Regression (MGWR) are employed to estimate the impacts of the urban land use on road traffic carbon dioxide emission. The basic form is exhibited as follows (Equation (3)),

$$y = \beta_0 + \sum_{k=1}^{n} \beta_k x_k + \varepsilon \tag{3}$$

where, β_0 represents the constant term, β_k is the estimated regression coefficient of variable k, and ε is the error term.

Unlike global regression models that assume spatial stationarity, the GWR model, as a local regression model, allows the estimation of spatially varying relationships by calibrating separate regression equations at each location. This enables the model to capture local variations in the influence of explanatory variables. The formula can be written as follows (Equation (4)),

$$y_i = \beta_0(u_i, v_i) + \sum_{k=1}^{n} \beta_k(u_i, v_i) x_{i,k} + \varepsilon_i \tag{4}$$

where, $\beta_0(u_i, v_i)$ represents the constant in the geographical unit (u_i, v_i), $\beta_k(u_i, v_i)$ is the estimated regression coefficient of variable k, and the ε_i is the error term in the geographical unit (u_i, v_i).

MGWR allows each explanatory variable to operate at its own spatial scale by assigning variable-specific bandwidths. The specific form can be written as follows (Equation (5)),

$$y_i = \beta_0(u_i, v_i) + \sum_{k=1}^{n} \beta_k(u_i, v_i, b_k) x_{i,k} + \varepsilon_i \tag{5}$$

where, b_k represents the bandwidth of the explanatory variable k, and other items are consistent with the GWR model.

This enables a more nuanced understanding of local variations and spatial heterogeneity in the influence of each factor. By capturing the multiscale spatial processes underlying the data, MGWR provides more accurate and interpretable results, offering critical insights for formulating region-specific policy interventions.

Remarkably, to ensure the robustness of the regression estimation, all variables were log-transformed. This transformation not only helps to mitigate heteroscedasticity in the data but also improves the overall model fit. Under this specification, the estimated coefficients represent elasticities, indicating the percentage change in the dependent variable associated with a 1% change in the independent variable. This facilitates a more meaningful comparison of impacts across different variables. Moreover, the use of logarithmic transformation enhances the model's robustness against outliers, thereby increasing the reliability and policy relevance of the findings.

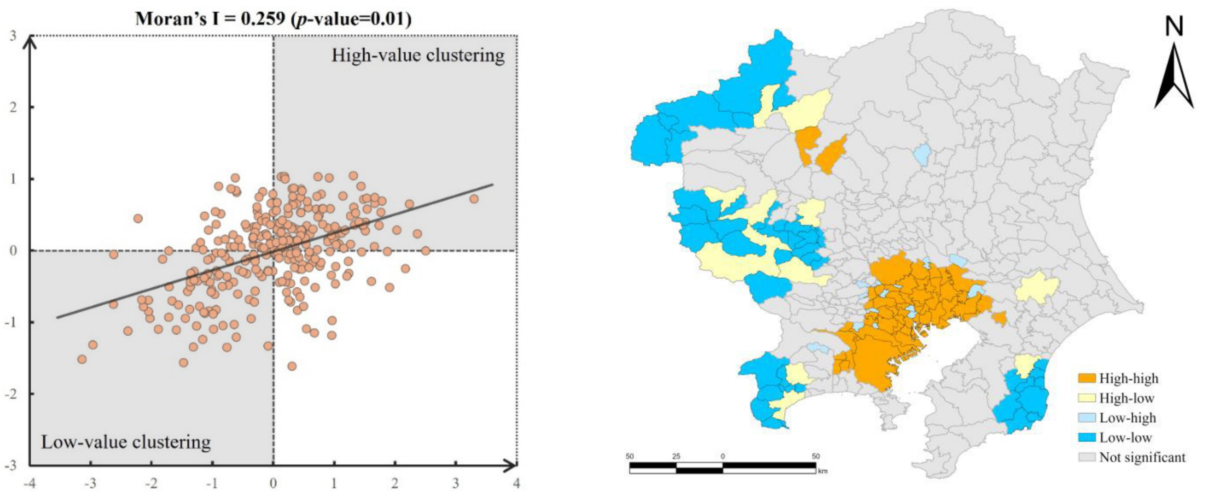
3. Results

3.1. Spatial Autocorrelation Analysis

The spatial autocorrelation results of road traffic carbon dioxide emissions are shown in **Figure 3**. The global Moran's I is 0.259 at the 99% confidence level. The Moran scatterplot exhibits most municipalities located in the first (high-value clustering) and third (low-value clustering) quadrants (see **Figure 3a**). These suggest that road traffic carbon dioxide emissions tend to exhibit spatial clustering characteristics. The LISA cluster map shown in **Figure 3b** reveals a clear pattern of spatial dependence. High-high cluster pattern (orange areas) is concentrated in the Tokyo metropolitan area and its surrounding municipalities, indicating that regions with high emission levels are geographically adjacent to each other. In contrast, low-low cluster pattern (blue areas) is predominantly located in the peripheral areas of western Saitama, western and southern Gunma, southwestern Chiba, and the southern edge of Kanagawa Prefecture, suggesting the existence of spatial agglomeration of low-emission municipalities. In addition, several municipalities are identified as spatial outliers, including high-low pattern (yellow areas) and low-high pattern (light blue areas), which imply the presence of spatial heterogeneity.

3.2. Model Performances of Regression Models

The model performances of the OLS, GWR and MGWR are presented in **Table 2**. Compared to the global regression model (OLS), the local regression models (GWR and MGWR), which account for spatial heterogeneity, exhibit higher adjusted R-squared values and log-likelihoods, along with lower AICc and RSS values [36]. Furthermore, the MGWR model, which employs dynamic bandwidth, outperforms the GWR model by improving model fit and log-likelihood by 2.1% and 13.9%, respectively, while also achieving the lowest AICc and RSS values. Overall, the MGWR model demonstrates the best performance among the three.



(**a**) (**b**)

Figure 3. The spatial autocorrelation analysis results of road traffic carbon dioxide emissions: (**a**) Global Moran's I; (**b**) LISA cluster map based on local Moran's I.

Table 2. Model performances.

	OLS	GWR	MGWR
Adj. R-squared	0.685	0.803	0.824
Log-likelihood	−255.673	−157.003	−135.181
AICc	525.720	447.465	423.208
RSS	95.068	49.988	45.004

We further analyzed the residuals of the OLS, GWR, and MGWR models. First, as shown in **Figure 4a–c**, the residuals of all three models approximately follow a normal distribution, indicating that the normality assumption is satisfied. Next, we conducted spatial autocorrelation analyses of the residuals for each model. As shown in **Table 3**, the OLS model yields a Z-score of 4.750 and a global Moran's I of 0.123, indicating a clustered spatial pattern significant at the 99% confidence level. In contrast, the GWR and MGWR models produce Z-scores of 0.035 and −1.431, respectively, suggesting that the null hypothesis of zero spatial autocorrelation cannot be rejected. This result is also visually supported by the Moran scatterplot in **Figure 4d**. The LISA cluster maps based on local Moran's I, shown in **Figure 4e–g**, reveal that the OLS model has the greatest number of spatially autocorrelated hotspots, while the MGWR model has the fewest. In summary, the MGWR model will be used for further effect analysis due to its superior performance.

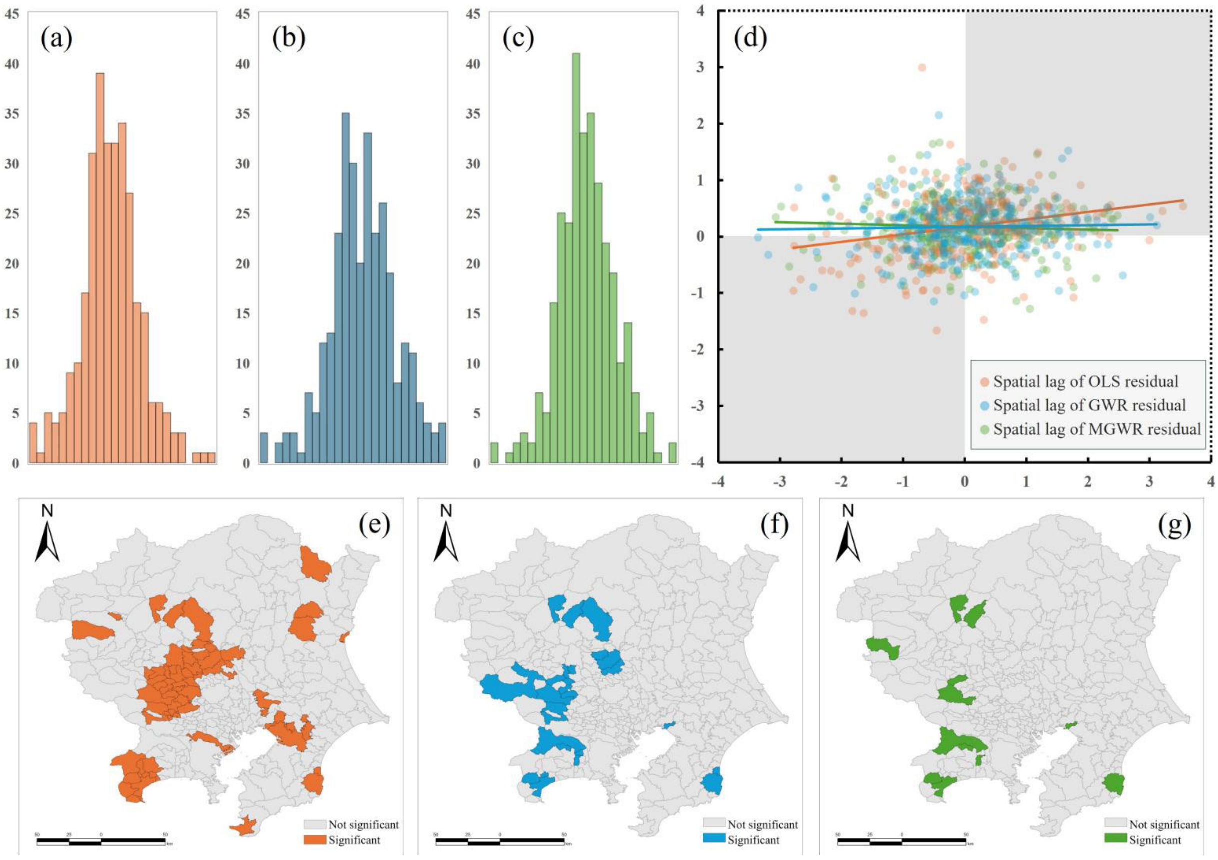


Figure 4. Residual analysis results of OLS, GWR and MGWR: (**a**) Histogram of OLS residuals; (**b**) Histogram of GWR residuals; (**c**) Histogram of MGWR residuals; (**d**) Moran scatterplots; (**e**) LISA cluster map of OLS residuals based on local Moran's I; (**f**) LISA cluster map of GWR residuals based on local Moran's I; (**g**) LISA cluster map of MGWR residuals based on local Moran's I.

Table 3. Spatial autocorrelation analysis for residuals of OLS, GWR and MGWR.

	OLS	**GWR**	**MGWR**
Moran's I	0.123	−0.002	−0.041
Z-score	4.750	0.035	−1.431
***p*-value**	0.000	0.972	0.152

3.3. Driving Effect of Urban Land Use

The overall adjusted R-squared value of the MGWR model is 0.824, indicating that the explanatory variables can explain 82.4% of the variance in road traffic carbon dioxide emissions (see **Table 4**). Nevertheless, the R-squared values still exhibit spatial variation. As illustrated in **Figure 5**, the local R-squared values in central Tokyo are below 0.75. In contrast, the surrounding areas, including western Tokyo, Saitama Prefecture, Kanagawa Prefecture, and Chiba Prefecture, generally show values above 0.80. In some regions of Tochigi, Gunma, and Ibaraki Prefectures, the R-squared values even exceed 0.90.

Table 4. The statistics of estimated coefficients of MGWR model.

	Estimated Coefficients of MGWR Model				
	Mean	**Std.**	**Min**	**Max**	**Sig. (*p*-Value < 0.05)**
PVN	0.072	0.001	0.071	0.072	100%
RND	0.087	0.001	0.086	0.087	100%
RLA	0.637	0.377	−0.208	1.261	87.30%
ILA	0.192	0.040	0.106	0.308	97.39%
CLA	0.402	0.030	0.290	0.457	100%

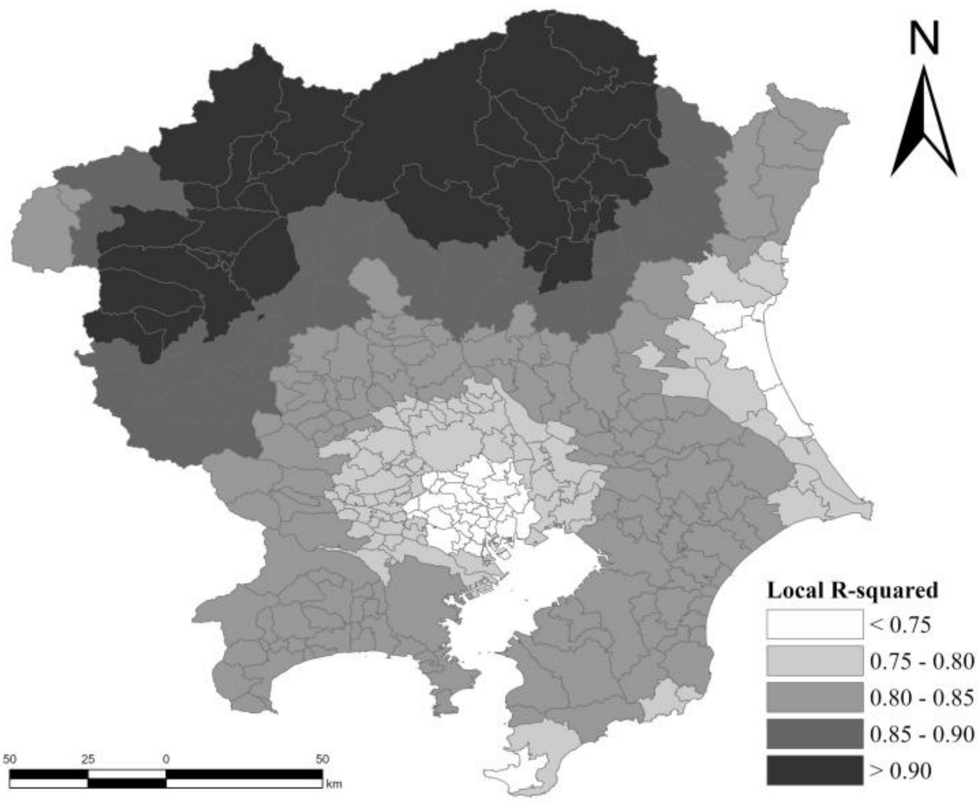


Figure 5. Local R-squared of MGWR model.

The estimated coefficients of the MGWR model for each explanatory variable are shown in **Table 4**. The results indicate that different explanatory variables exhibit varying effects on the dependent variable. Among them, PVN and RND, as control variables, exhibit statistically significant effects at the 95% confidence level, with mean coefficients of 0.072 and 0.087, respectively, and a standard deviation of only 0.001. Specifically, the elasticity estimates indicate that a 1% increase in per capita vehicle ownership is associated with an average increase of approximately 0.07%

in road traffic carbon dioxide emissions. Similarly, a 1% increase in road network density corresponds to an average emission increase of about 0.09%. This suggests that their positive influence on road traffic carbon dioxide emissions is highly consistent across all municipalities and spatially stable.

In contrast, indicators related to urban land use display notable spatial variation in their effects. Specifically, RLA exhibits significant impacts in 87.30% of municipalities, and the standard deviation of 0.377 indicates a strong degree of spatial heterogeneity in its impact on road traffic carbon dioxide emissions. It is worth noting that the minimum estimated coefficient is negative, implying that RLA may exert a suppressive effect on emissions in certain areas.

The coefficients of ILA and CLA also show a certain degree of spatial variability. The mean coefficient of ILA is 0.192 with a standard deviation of 0.040, and it is statistically significant in 97.39% of municipalities. CLA has a mean coefficient of 0.402, a standard deviation of 0.030, and shows statistical significance (p-value < 0.05) in all municipalities.

Spatial distributions of land use variable coefficients are exhibited in **Figure 6**. The spatial variation in the effect of RLA is shown in **Figure 6a**. A distinct pattern emerges wherein the central and northeastern parts of the region, covering spatial wards of Tokyo, eastern Saitama, and northern Ibaraki, exhibit the strongest positive coefficients. In contrast, the western and southern parts of the region, including parts of Gunma, Yamanashi, and southern Kanagawa, show weaker or statistically insignificant associations.

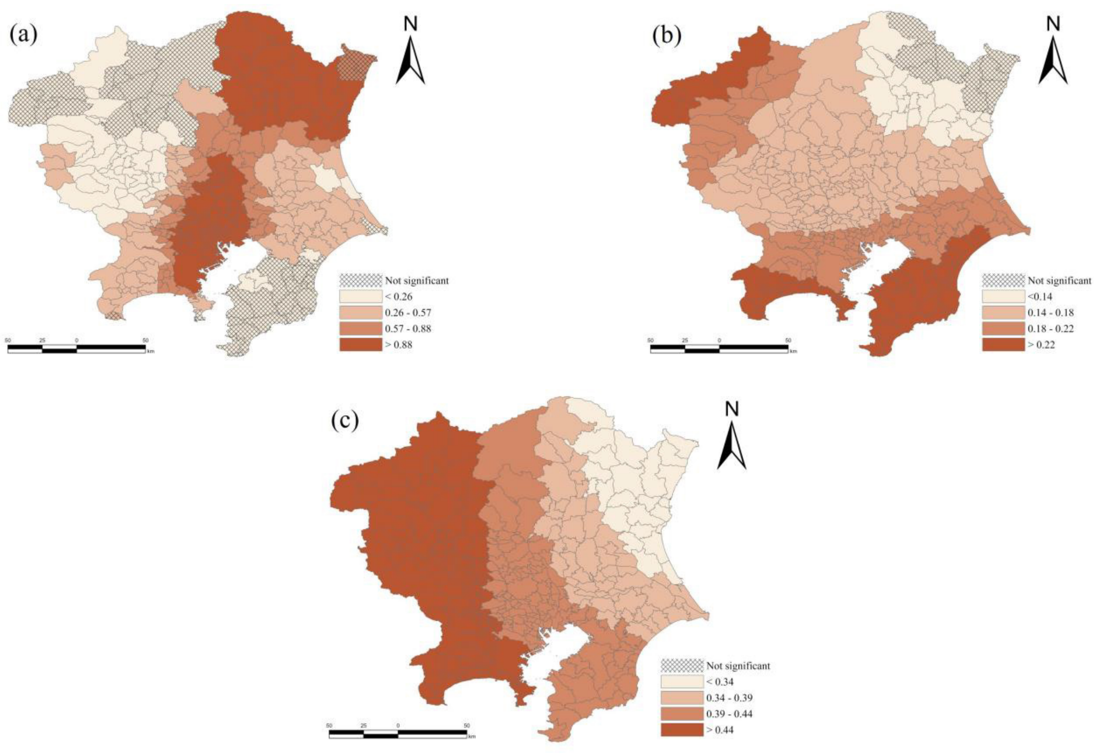


Figure 6. Spatial variations of MGWR estimated coefficients: (**a**) RLA; (**b**) ILA; (**c**) CLA.

Figure 6b presents the spatial distribution of the regression coefficients for industrial land area. The highest coefficients (>0.22) are clustered in southern Chiba and Kanagawa, as well as in the inland mountainous regions of Gunma and Saitama. Conversely, the northeastern part of the study area, notably in northern Ibaraki and Tochigi, displays non-significant or relatively weak associations (<0.14).

As illustrated in **Figure 6c**, the regression coefficients are higher in the western part of the study area, particularly in Saitama, western Tokyo, and western Kanagawa, where values exceed 0.44. In contrast, the coefficients decrease moving eastward, particularly in Chiba Prefecture and eastern Ibaraki, where the values are below 0.34.

4. Discussion

Urban land use plays a crucial role in shaping patterns of road traffic carbon dioxide emissions. Different land use types influence travel demand, traffic flow patterns, and ultimately emission intensity. For instance, high-density residential areas typically generate shorter but more frequent trips, while low-density suburban development often leads to longer commuting distances and greater dependence on private vehicles [37–39]. The location and concentration of commercial and industrial areas can also affect the spatial distribution of traffic, thereby influencing congestion levels and emission intensity. In addition, the spatial organization of land use, including the degree of land use mix and the physical distance between residential, employment, and service functions, has a direct impact on travel behavior. These factors affect the choice of transportation modes, trip frequency and duration, and the overall carbon output associated with urban mobility. A comprehensive understanding of the relationship between land use structure and transportation emissions is therefore essential for formulating effective urban planning policies that encourage compact development, improve accessibility, and support low-carbon transport systems.

Various studies have consistently shown that, despite differences in emission mechanisms and spatiotemporal characteristics across various sectors, carbon dioxide emissions often exhibit spatial clustering [40–43]. The results of this study further support this idea by demonstrating that road traffic carbon dioxide emissions also display significant spatial aggregation at the municipal level, thereby providing new empirical evidence at a finer spatial resolution. Additionally, the LISA analysis also identifies a small number of high-low and low-high spatial outliers, indicating that local emission levels are not always consistent with those of neighboring municipalities. These anomalies may be related to localized functional characteristics, such as major transport or logistics facilities, specialized economic activities, or distinctive commuting relationships with surrounding areas. Although limited in number, such outliers highlight the localized complexity of emission-driving mechanisms and complement the overall pattern of spatial heterogeneity. A comparison between global models and those incorporating spatial weights reveals that the inclusion of spatial effects improves model fit by approximately 12%, indicating the substantial influence of spatial variations on emission behaviors. Moreover, the comparison between fixed and adaptive bandwidths suggests that traditional model evaluation metrics, such as goodness-of-fit or residual normality, are insufficient to distinguish between the two. This highlights the necessity of examining the local spatial autocorrelation of model residuals to detect potential spatial outliers or structural biases.

The local adjusted R-squared values of the MGWR model exhibit a gradually increasing trend outward from the central area of Tokyo, indicating stronger explanatory power in surrounding regions and relatively lower goodness-of-fit in the urban core. Similar patterns have been reported in previous studies [26,44]. This result suggests that road traffic carbon dioxide emissions in central Tokyo are influenced by a more complex set of mechanisms, for which land-use structure alone provides a limited explanation. The spatial wards of Tokyo are characterized by highly complex and mixed land-use configurations, accompanied by diversified transportation systems that include a substantial share of non-motorized travel, an extensive rail transit network [45–47]. In such contexts, additional factors such as traffic management practices, vehicle fleet characteristics, and heterogeneous socioeconomic activities are likely to play a more prominent role in shaping emission outcomes, thereby reducing the relative explanatory contribution of land-use variables captured by the MGWR model [48–51]. In contrast, peripheral municipalities tend to exhibit more homogeneous land-use patterns, higher dependence on private motor vehicles, and more structured road networks. Under these conditions, changes in local land-use structure are more directly translated into variations in road traffic carbon dioxide emissions, resulting in higher local explanatory power. This contrast further reinforces the spatial heterogeneity identified in the analysis, indicating that both the strength and relevance of land-use effects vary systematically across urban contexts.

Given the high urbanization of the Kanto region of Japan, where the tertiary sector is highly developed and the primary sector accounts for only a minimal proportion, this study focuses on the impacts of residential, industrial, and commercial land use at the municipal level on urban road traffic emissions, while excluding agricultural land use from the analysis. It is worth noting that per capita motor vehicle ownership and road network scale are typically regarded as key factors in the analysis of road traffic carbon dioxide emissions [26,32]. The former reflects the degree of dependence on motorized travel and serves as a direct indicator of carbon emission sources, while the latter represents the capacity and connectivity of the regional transportation infrastructure, which also significantly affects the level of road traffic carbon dioxide emissions. Even after incorporating both variables into the model as explanatory factors, residential, industrial, and commercial land use still exhibits significant spatial effects on traffic carbon dioxide emissions. This finding suggests that different land use types are associated with variations in travel behavior, traffic flow intensity, and vehicle operating efficiency. Therefore, in the formulation of carbon reduction policies, it is essential to consider the spatial characteristics of land use structures and to optimize land use configurations accordingly, to promote a low-carbon transformation of urban transportation systems.

The regression model results indicate that the expansion of residential, industrial, and commercial land use is generally associated with varying degrees of increase in road traffic carbon dioxide emissions. However, the results from the MGWR model further reveal the impacts of these three land use types on emissions. It is particularly worth noting that, compared to industrial and commercial land use, residential land use plays a decisive role in intensifying road traffic carbon dioxide emissions. From a climate governance perspective, the identification of residential land use as the most decisive factor has direct implications for long-term carbon reduction strategies. Residential land structure fundamentally shapes daily mobility demand, commuting distance, and travel mode dependence, making it a critical leverage point for transportation decarbonization. Therefore, understanding its spatially varying role is essential for aligning urban land-use planning with broader climate objectives, including carbon peaking and carbon neutrality targets. Hence, emission reduction efforts should not focus solely on industrial or commercial planning, but prioritize improving land-use mix, optimizing residential location allocation, and enhancing public transport accessibility in residential zones, particularly in emission-intensive areas. Spatially differentiated strategies should be adopted to reflect the uneven impact of residential land use across regions [52,53]. Moreover, the influence of residential land also displays the highest degree of spatial variability. This indicates that its impact on road traffic carbon dioxide emissions is highly uneven across different spatial units, and that the underlying mechanisms are shaped by a combination of factors, including urban spatial structure, population density, transportation accessibility, and the distribution of jobs and housing [54,55]. Specifically, in densely populated areas with concentrated urban functions, residential land use tends to generate more frequent travel activities, thereby exerting a stronger influence on road traffic carbon emissions. In contrast, in peripheral or suburban areas, although residential land may be expanding, the relatively dispersed urban functions and lower travel demand lead to weaker marginal effects on emissions [56,57]. Notably, the negative coefficients associated with residential land use in some peripheral cities indicate that residential expansion does not necessarily intensify road traffic carbon dioxide emissions in all locations. One plausible explanation is the presence of relatively self-sufficient satellite cities, where residential areas are increasingly matched with local employment opportunities and daily services. Under such conditions, additional residential land may not induce long-distance commuting, thereby weakening automobile-dependent travel demand. In contrast, in relatively less developed areas, commercial land expansion is more likely to concentrate on activities and attract automobile-dependent trips, leading to a stronger positive impact on road traffic carbon dioxide emissions. This spatial pattern reflects diminishing marginal traffic impacts of commercial land in mature urban systems and highlights the role of functional decentralization within a polycentric urban framework. Overall, the pronounced spatial heterogeneity of residential land-use effects reflects variations in local residential patterns, particularly differences in job-housing balance, automobile dependence, and the spatial organization of daily activities across municipalities.

Therefore, when formulating low-carbon transportation policies and optimizing urban land use strategies, it is essential to consider the spatial characteristics of residential land, and the travel behavior patterns within different regions. Only through targeted and context-specific measures can we effectively curb the continuous growth of road traffic carbon dioxide emissions and promote sustainable urban development.

5. Conclusions

This study systematically examined the spatial distribution characteristics of road traffic carbon dioxide emissions at the municipal level in the Kanto region of Japan and analyzed the spatial effects of different urban land use types on these emissions by constructing a multi-scale geographically weighted regression (MGWR) model. The results indicate that road traffic carbon dioxide emissions exhibit significant spatial clustering, characterized by high-value clusters in central Tokyo and low-value clusters in surrounding areas. Estimates from OLS, GWR, and MGWR models show that residential, industrial, and commercial land uses all have significant driving effects on road traffic carbon dioxide emissions, but the intensity of these impacts varies substantially across space. Among them, residential land use not only has the largest impact coefficient but also demonstrates the strongest spatial variability, making it a decisive factor influencing road traffic carbon dioxide emissions.

Based on these findings, which reveal pronounced spatial heterogeneity in land-use effects, the following policy implications are proposed to support more effective and place-based road traffic carbon mitigation strategies. Specifically, the identified spatial heterogeneity in land-use effects implies that road traffic carbon dioxide mitigation policies should adopt a place-based approach rather than uniform interventions across the metropolitan region. In core urban areas, such as the central wards of Tokyo, where commercial land use plays a dominant role, policy priorities should focus on managing automobile travel demand associated with commercial and service activities, emphasizing transport efficiency and demand management rather than further road expansion. In suburban and peripheral municipalities, such as parts of western Saitama, Chiba, and outer areas of Kanagawa, where residential land use is the primary and most variable driver, mitigation strategies should prioritize guiding residential land development toward forms that reduce car-dependent commuting, with particular attention to aligning residential growth with local travel conditions. Given the strong and uneven influence of residential land use across municipalities, residential land-use planning should be treated as a key policy lever in low-carbon transportation strategies, and its regulation should be adapted to local urban functions and spatial contexts. It should be noted that the MGWR coefficients estimated in this study reflect a cross-sectional snapshot based on 2021 data. In the Japanese context, urban development has entered a relatively stable stage, and annual changes in municipal land-use patterns are generally limited, which helps mitigate potential short-term variability in the estimated relationships. Nevertheless, as urban structure, transport systems, and travel behavior evolve over longer time horizons, the magnitude and spatial configuration of these relationships may change, implying that long-term planning decisions should interpret the results as context-specific rather than temporally invariant.

While this study provides robust evidence on the spatially heterogeneous effects of urban land use on road traffic carbon dioxide emissions, several aspects warrant further exploration. The analysis is based on cross-sectional data for a single year, which limits the examination of temporal dynamics in land-use structure and travel behavior. In addition, some factors that may influence road traffic emissions, such as public transport accessibility and fuel price variation, are not explicitly incorporated due to data availability considerations. Future research could extend this work by applying the MGWR framework to other metropolitan regions to assess the broader applicability of the findings. Incorporating longitudinal data would help capture temporal changes in land-use effects, while the use of finer-grained spatial data and more detailed transport-related indicators could further refine the understanding of the mechanisms identified in this study.

Focusing on the spatial relationship between urban land use structure and road traffic carbon dioxide emissions, this study highlights the dominant role of different land use types—particularly residential land—in shaping emissions and their pronounced spatial heterogeneity. By applying the MGWR model, the analysis identifies key influencing factors at local scales, thereby enhancing the spatial resolution of emission mechanism interpretation. More importantly, the findings underscore that effective road traffic carbon mitigation and transportation decarbonization cannot rely solely on uniform technological solutions, but require spatially informed land-use strategies that reflect local urban functions and mobility patterns. In this regard, recognizing the decisive and spatially varying role of residential land use provides a structural basis for aligning urban planning and transportation policies with long-term climate mitigation objectives, including carbon neutrality. Overall, the study offers a scientific foundation for formulating location-specific policies that promote the coordinated optimization of low-carbon transportation systems and urban land use.

Author Contributions

Conceptualization, Y.Y. and J.J.; methodology, Y.Y.; software, Y.Y.; validation, J.J., Y.X., and Y.C.; formal analysis, Y.Y. and J.J.; investigation, Y.Y.; resources, Y.Y.; data curation, Y.Y. and J.J.; writing—original draft preparation, Y.Y.; writing—review and editing, J.J., X.J., H.X. and Y.C.; visualization, Y.X.; supervision, X.J. and Y.C.; project administration, Y.C.; funding acquisition, Y.C. and J.J. All authors have read and agreed to the published version of the manuscript.

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The raw data supporting the conclusions of this article will be made available by the authors on request.

Conflicts of Interest

The authors declare no conflict of interest.

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