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The Carbon Emission Implications of Intensive Urban Land Use in Emerging Regions: Insights from Chinese Cities

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Abstract: Intensive urban land use is a strategy to enhance productivity and mitigate environmental challenges in emerging regions, but its relationship with carbon emissions needs further city-level investigation. This study investigates the impact of intensive urban land use on carbon emissions across 153 cities in China, thus employing the STIRPAT model with the ordinary least square (OLS) and geographical weighted regression (GWR) methods. The findings underscore the heterogenous influence of intensive urban land use on carbon emissions across China's urban landscapes: (1) R&D investment intensity and population density show significant negative association with carbon emissions in general. (2) Capital investment intensity positively affects carbon emissions in low-income cities, R&D investment intensity shows negative effects on carbon emissions in middle-income cities, and population density emerges as a substantial factor in reducing carbon emissions in both middle- and low-income cities. (3) Capital intensity, labor intensity, and R&D investment intensity exert positive effects on emissions in middle China and negative influences in northeastern and southern China, whereas population density shows converse spatial effects. Based on the study's results, tailored policy implications are provided for urban planning authorities in emerging regions.

Keywords: carbon emissions; intensive land use; developing regions; China

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1. Introduction

Cities are the most important carbon emitter, thereby generating about 75% of carbon dioxide (CO_2) [1,2]. As cities expand, urbanization accelerates, thus resulting in heightened energy consumption, increased transport demands, and intensified industrial activities. In particular, fast-growing cities in emerging countries have experienced unprecedented expansion: 440 emerging-market cities will account for close to half of expected global GDP growth by 2025 [3]. The rapid urbanization is often associated with unplanned growth, thus resulting in congestion, sprawling suburbs, inefficient land use, and greater reliance on fossil fuels [4]. These emerging urban areas are becoming focal points for greenhouse gas (GHG) production, thus leading to deteriorating urban microclimates, decreased urban population well-being, a reduced quality of life, and risking regional sustainable development.

Consequently, for cities in emerging markets, the formulation of sustainable land use strategies assumes paramount importance. These strategies play a critical role in mitigating carbon emissions intensity while simultaneously balancing economic growth with environmental resource demands [4–6]. Among the promising land use approaches, intensive urban land use stands out [5,7]. This strategy involves concentrating activities, populations, and infrastructure within a confined geographical area. Theoretically, it enhances land use efficiency through practices such as mixed-use zoning and compact development, thereby reducing the overall land area required for urban functions [8]. Consequently, it curtails the conversion of natural areas and preserves carbon-storing ecosystems. Additionally, intensive urban land use contributes to the reduction of intracity travel distances, promoting industrial process efficiency and encouraging sustainable transport modes like cycling and public transits [9], and ultimately leading to decreased urban carbon emissions.

Over the past few decades, intensive land use has been widely adopted, particularly in emerging Asian countries [7]. However, as more research focuses on the carbon emissions impact of this strategy, debates on this topic are gaining attention from the academic community and urban policymakers [8–10]. Various studies, each concentrating on specific areas, hold divergent views. Some research suggests that this strategy can curb urban carbon emissions through compact and resource-efficient design. For instance, Xie et al. [11] reported an inhibitory effect of intensive urban land use indicators (research and development, labor, and capital intensity) on carbon emissions. Based on a case of Jiangsu coastal region, Chuai et al. [10] also support the strategy of intensive land use, such as restricting the conversion of agricultural and forest land to urban development, which can mitigate urban carbon emissions. However, other studies question the actual effectiveness of the intensive urban land use strategy. Wang et al. [12] found a positive correlation between land use intensity (economic, population, infrastructure, and public service intensity) and carbon emissions.

Understanding the carbon emission implications of intensive urban land use in rapid-developing regions is crucial for addressing the environmental challenges associated with urbanization. By identifying the key sources and drivers of carbon emissions in these regions, policymakers, urban planners, and stakeholders can develop targeted strategies and interventions to promote sustainable urban development and mitigate the negative environmental impacts. There is a lack of city-level evidence to examine the impact of multidimensional land use intensity indicators on carbon emissions, especially with the consideration of regional heterogeneity. This study is the first attempt to examine the heterogenous city-level implication of comprehensive land use intensity indicators on carbon emissions. Specifically, the research purposes include the following: (1) identifying the intensive urban land use indicators, (2) revealing the impacts of the intensive urban land use indicators on carbon emissions and the regional differences among their effects, and (3) developing carbon emission interventions from perspectives of urban land use intensity. To explore the impact of intensive urban land use on carbon emissions, this research incorporates representative urban land use intensity indicators into the STIRPAT (Stochastic Impacts by Regression on Population, Affluence, and Technology) model using data from 153 cities in China.

This research can quantify potential regional differences in the effects of intensive land use indicators on carbon emissions, thus allowing for targeted policy interventions. The urban development trajectory of China holds important lessons for mitigating the environmental impacts of urbanization for other emerging economies. This study provides evidence-based recommendations for policymakers and urban planners to optimize urban land use intensity and promote low-carbon development strategies. Also, the findings can inform targeted policy interventions tailored to cities with different development levels, thus considering the heterogeneity of the impacts of intensive land use indicators.

2. Literature Review

Urban land use intensity refers to the measure of the level of human activity and development within a specific area of urban environment [13]. Urban land use intensity is typically evaluated based on several indicators, including population density, building density, infrastructure density, and economic activity levels. Intensive land use, in the context of urban areas, refers to the high-density development and concentration of human activities within a given area [14]. It is characterized by a high population density, dense building patterns, and a significant presence of commercial, industrial, and transportation infrastructure. Cities like Hong Kong and Singapore have provided successful examples of the intensive land use concept during the latter part of the 20th century [7].

Intensive land use is often associated with the efficient utilization of urban space; however, evidence shows that it can also have significant implications for urban carbon emissions. Previous research has shown interacting links between urban land use intensity and CO_2, thus encouraging the development of compact urban forms with high population densities. Most of these studies focus on population density, which is one of the aspects of urban land use intensity, while ignoring the other dimensions. For example, Yi, Wang [15] explored the carbon emission effect of urban density and found that a significant negative correlation existed between urban density and carbon emissions. In addition, the impacts varied among cities of different sizes. Zhang, Wang [16] found that population density was a big factor in restraining carbon emissions. Kang et al.'s [17] results show the land use intensity had a bidirectional correlation with carbon emissions in most cities, but the negative effect progressively spread. Liang el. al. [18] identified an inverted U-curve association between carbon footprint and land use intensity at the middle and low quartiles, while population clustering promoted carbon footprint mitigation at the upper quartiles. Xiao et al. [19] discovered that land use intensity increased urban building carbon emissions under new-type urbanization construction. Feng and Zhou [20] found that land use intensity has a significant positive effect on carbon emissions per unit of GDP. Though some studies developed indicators from multiple dimensions, e.g., Wang [12] selected the proportion of built districts, urban construction, land use for living, land use for production, land use for infrastructure, and information entropy of the land use structure, they have still restricted the definition of intensity with respect to density. Xie [11] explored the impacts of intensive land use on carbon emission reduction at a provincial level in China; labor intensity, capital intensity, energy intensity, and R&D investment intensity were used to represent the land use intensity metric. Similarly, only one dimension—the land input level—was incorporated into the evaluation framework.

To fully understand the environmental implications of intensive land use, several studies have adopted the input–density–output definition in describing the causal relationship. Hui, Wu [21] applied these three dimensions to evaluate urban land-intensive utilization. The land input level was represented by investment, wage, and energy consumption, the land use density was measured by population density and construction land area per capita, and the land output benefit was evaluated using the GDP, industrial added value, and green area per unit of urban land or capita. The work studied the relationship between urban scale expansion and land use intensity. Xia, Dong [22] used fixed assets investment and labor wage input per unit of urban land to represent the land input level, urban population density to describe the land use density, and GDP per unit of urban land as the indicator for the land output benefit; the work analyzed the spatial effect of urban land use intensity on carbon emissions using the spatial Durbin model.

Though the environmental implications of intensive urban land use have been explored, there still exist research gaps. Firstly, there is a lack of city-level evidence to examine the impact of land use intensity on carbon emissions. Secondly, few studies have investigated the heterogeneous implications among different regions. To summarize, systematic research examining the effects of urban land use intensity on carbon emissions with the consideration of heterogeneity among cities is needed.

3. Method

The research framework diagram is shown in Figure 1. This study applied an input-density-output framework to evaluate urban land use intensity and the STIRPAT model to analyze its association with carbon emissions. Both the OLS and GWR models were used to test the impacts. Finally, tailored policy implications have been proposed based on the regression results.

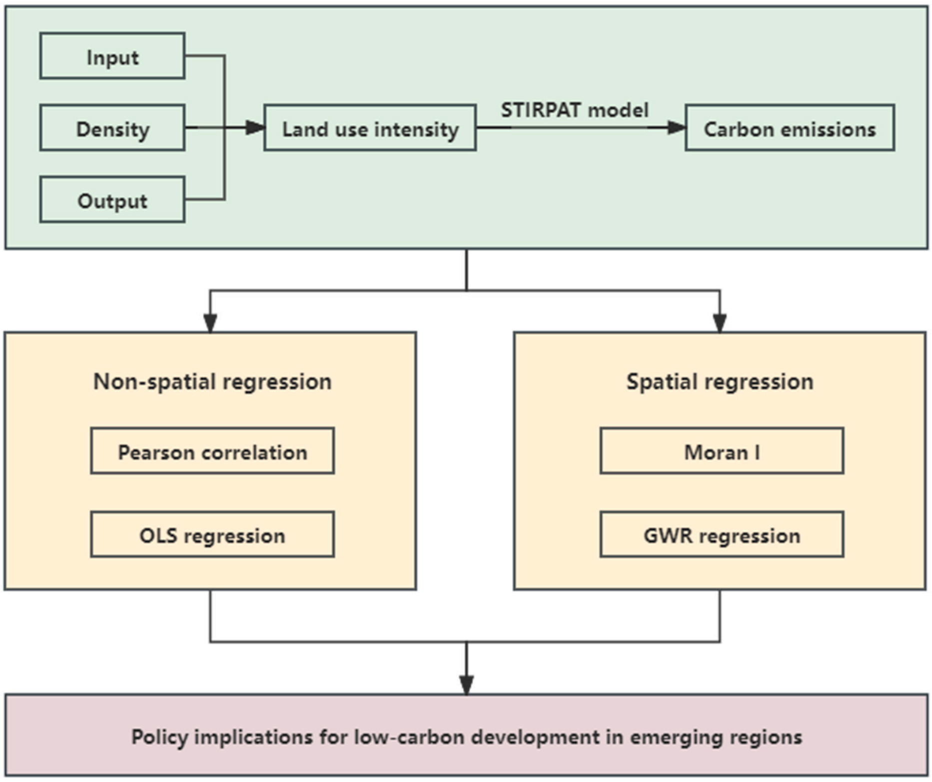

Figure 1. Research framework diagram.

3.1. Study Area

China is a typical emerging-market country that has experienced unprecedented urbanization over the past few decades, thus marked by rapid economic growth and massive rural-to-urban migration. China's urban landscape has undergone dramatic changes, with cities expanding both vertically and horizontally to accommodate the influx of people and economic activities [23]. The rapid pace of urbanization in China has raised concerns about its environmental impact, particularly in terms of carbon emissions. Recognizing the challenges posed by rapid urbanization, the Chinese government has emphasized the need for sustainable urban development strategies. Intensive urban land use has emerged as a promising approach to promoting compact, efficient, and environmentally friendly urban growth [24–26]. By optimizing land use patterns, reducing sprawl, and improving infrastructure efficiency, intensive urban development aims to mitigate environmental impacts while supporting economic growth and social well-being. The "Land Saving and Intense Usage Rules" published by the Ministry of Land and Resources outlined a fundamental "Five Regulations" policy of slower expansion, inventory optimization, flow efficiency, and quality enhancement [27]. By increasing the effectiveness of industrial inputs, enabling the treatment of pollutants, or reducing commuting time, intensive urban land use might aid in the construction of low-carbon cities [16,25].

3.2. Data Description

Based on the literature review and data availability, this study adopted the input–density–output framework to describe the urban land use intensity. Capital intensity, labor intensity, and R&D investment intensity were selected as the land input levels. Population intensity was selected to define the land density. Economic output per unit land area was regarded as the land output intensity.

The data used in this study include the carbon emissions, urban land area, GDP, population, number of labors, research and development investment, gross investment in fixed assets, and energy consumption of the sample cities. The data sources are described in Table 1.

Table 1. Data sources.

Data	Source
Carbon emissions	China Emission Accounts and Data Sets (CEADs)
Urban land area	Land survey results sharing application service platform developed by Ministry of Natural Resources in China
GDP Population Wage of labors R&D investment Gross investment in fixed assets	China City Statistical Yearbook
Energy consumption	[28]

Given the heterogeneity of development levels among China's cities, we divided the cities into three groups based on their development level, which was measured by per capita GDP: this yielded a high development level, middle development level, and low development level. According to data availability, 153 cities were selected as sample cities.

The data descriptive statistics are shown in Table 2. The wide range of carbon emissions, socioeconomic data, and land use intensity levels among cities, as indicated by the substantial standard deviations, suggests disparities in environmental performance and sustainability practices across urban areas. The data description underscores the importance of categorized exploration with consideration of city heterogeneity and targeted policy interventions tailored to the specific characteristics and challenges faced by individual cities.

Table 2. Data descriptive statistics.

VarName	Description	Unit	Mean	SD	Min	Median	Max
CE	Carbon emissions	10^6 tons	52.148	63.152	1.804	33.167	457.757
POP	Population	10^6 persons	3.990	3.897	0.720	2.550	22.290
PCGDP	Per capita GDP	10^4 yuan	101.368	36.691	25.476	93.267	208.464
EC	Energy consumption intensity	ton/10^4 yuan	60.141	41.129	8.036	49.403	298.600
KI	Capital intensity	10^4 yuan/km^2	62,798.369	24,691.143	5373.225	60,672.016	142,505.728
LI	Labor intensity	10^4 yuan/km^2	14,944.241	18,862.591	4419.651	10,665.803	191,161.483
RI	R&D investment intensity	10^4 yuan/km^2	455.877	487.395	14.318	325.203	3663.048
PI	Population intensity	Persons/km^2	8965.525	2510.175	3668.224	8781.204	19,151.251
OI	Land output intensity	10^4 yuan/km^2	89,843.150	39,425.188	13,276.021	81,801.656	292,739.561

Data of carbon emissions and intensive urban land use indicators are presented in spatial distribution in Figure 2. It is shown that the emissions and land use intensity vary across regions greatly, which indicates a huge development gap among cities. Cities in western China, which are usually regarded as lagging development regions, have high carbon emissions, with high capital intensity and R&D investment intensity. On the contrary, cities in eastern coastal China, which have good economic conditions, present high urban land use intensity and low emissions.

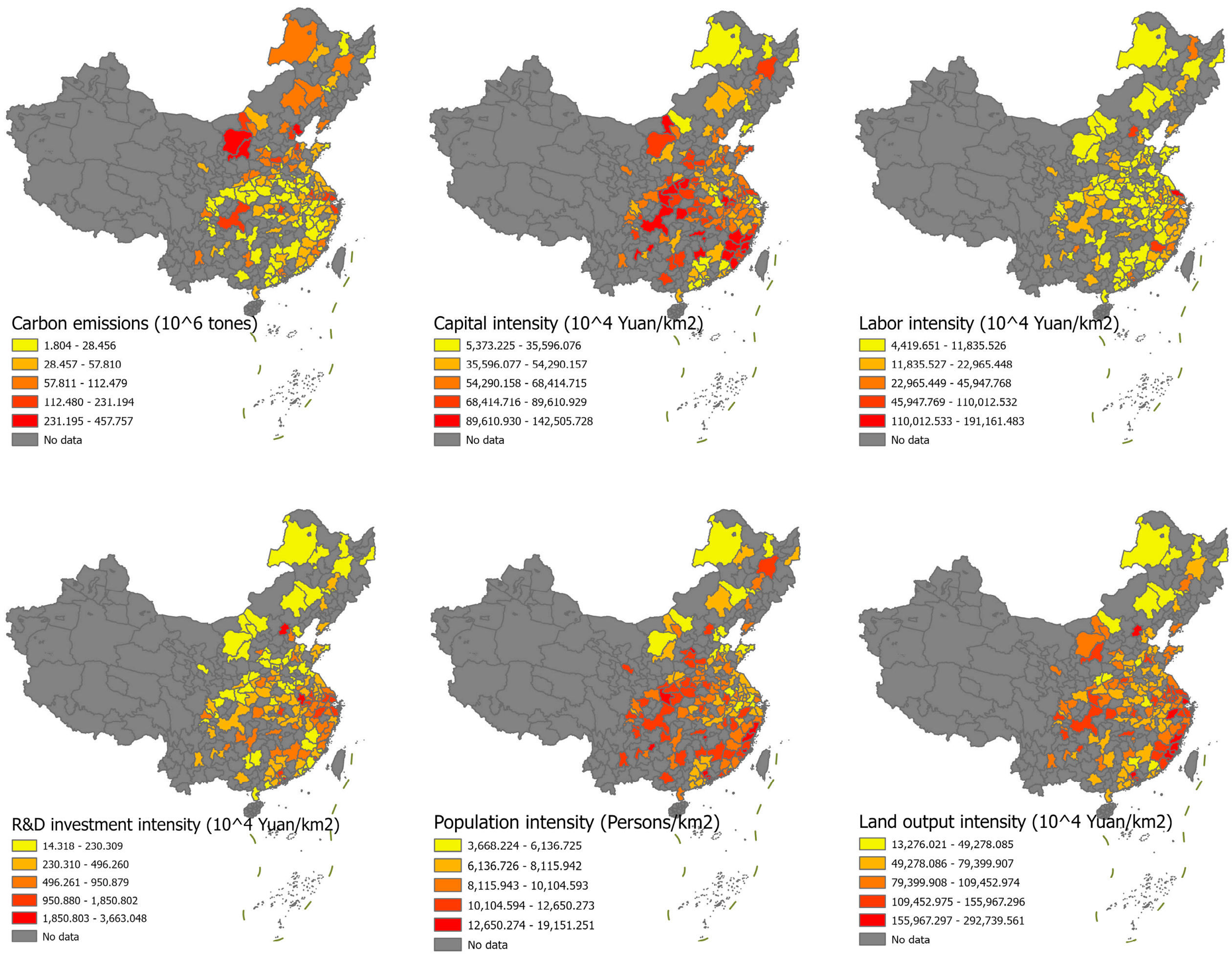

Figure 2. The distribution of carbon emissions and intensive urban land use indicators in China's cities.

3.3. Model Development

The STIRPAT model, an acronym for "Stochastic Impacts by Regression on Population, Affluence, and Technology", has gained widespread popularity in assessing environmental impacts and identifying the factors that influence carbon emissions [29,30]. This multiplicative model is built upon the IPAT identity, which posits that environmental impact is the product of population, affluence, and technology factors. By utilizing the STIRPAT model, researchers in environmental studies can effectively examine the relationship between population, economic development, and environmental impact factors. One significant advantage of the STIRPAT model, when compared to other approaches such as the IPAT model, is its flexibility in incorporating representative drivers from various perspectives [31–34]. For instance, factors such as land use and urbanization can be integrated into the model based on the specific requirements of the study. This allows for a more comprehensive analysis of the relationships between population, economic factors, and environmental impact. As a result of its ability to encompass diverse drivers, the empirical findings derived from the STIRPAT model tend to be more reasonable and credible. Researchers can tailor the model to their specific research context, thus ensuring that relevant factors are included and contributing to a more accurate understanding of the complex dynamics between population, economic development, and environmental outcomes.

This study used the STIRPAT model to analyze the impact of intensive urban land use on carbon emissions in China's cities. The specification of the STIRPAT model can be expressed as follows:

$$I_i = aP_i^b A_i^c T_i^d e_i \tag{1}$$

In the model, the constant term a serves as a scaling factor, while the exponents b, c, and d represent the respective powers of the variables P, A, and T, which are estimated. Additionally, the error term "e" accounts for unexplained variation. The subscript i signifies that these variables (I, P, A, T, and e) vary among different observational units.

An additive regression model in which all variables are in logarithmic form facilitates estimation and hypothesis testing:

$$\ln I = a + b\ln P + c\ln A + d\ln T + \ln e \tag{2}$$

In this equation, the coefficients b, c, and d represent the proportional changes in environmental impacts for each 1% change in population size, wealth level, and technology level.

With the representative drivers of intensive land use indicators added into the model in this research, the extended STIRPAT model with the ordinary least squares (OLS) method is denoted as follows:

$$\begin{aligned}\ln CE =& \alpha_0 + \alpha_1 \ln POP + \alpha_2 \ln PCGDP + \alpha_3 \ln EC \\ &+ \alpha_4 \ln LI + \alpha_5 \ln KI + \alpha_6 \ln RI + \alpha_7 \ln PI + \alpha_8 \ln OI + \ln e\end{aligned} \tag{3}$$

where α_0 denotes a constant; e denotes the error term; CE, POP, PCGDP, EC, LI, KI, RI, PI, and OI denote the carbon emission, population, per capita GDP, energy use intensity, labor intensity, capital intensity, R&D investment intensity, population density, economic output intensity, respectively; and α_1, α_2, . . ., and α_8 represent the parameters to be estimated.

The OLS model is a global parameter estimation technique that can only represent the average contribution, because it assumes invariant coefficients [35]. However, carbon emissions and their determinants have a tendency to be geographically autocorrelated [36,37]. The spatial nonstationarity of geographic elements is ignored by the OLS model, which can easily provide biased findings or ineffective estimations [38]. The geographical weighted regression (GWR) model can describe the spatial characteristics of impacts, while spatial heterogeneity is taken into account by conducting local estimation [39]. The GWR model can be expressed as follows:

$$\mathrm{y_i} = \beta_0(\mathrm{u_i, v_{i,}}) + \sum_{\mathrm{j=1}}^{\mathrm{k}} \beta_{\mathrm{j}}(\mathrm{u_i, v_{i,}})\mathrm{X_{ij}} + \mathrm{e_i} \tag{4}$$

where $\mathrm{y_i}$ is the carbon emissions, and $\mathrm{X_{ij}}$ are the jth independant variables at location i. β_0 and β_j are the estimated coefficients at location i; $(\mathrm{u_i, v_{i,}})$ are the coordinates of location i, and $\mathrm{e_i}$ is the random error at location i.

4. Empirical Results

This section begins by presenting the findings of a Pearson correlation test, which aims to uncover the relationships between the variables under investigation. Subsequently, the regression results are provided, thus offering additional insights into the associations among the variables.

4.1. Correlation between Variables

As shown in Table 3, this study applied correlation analysis to uncover the interrelationships among the variables and to identify any significant associations that may exist. The results show that carbon emissions (lnCE) had a positive correlation with population (lnPOP) (r = 0.524, p < 0.001). This suggests that cities with larger populations tend to have higher carbon emissions. lnCE exhibited a positive correlation with per capita GDP (lnPCGDP) (r = 0.363, p < 0.001), thus indicating that cities with higher per capita GDPs tend to have higher carbon emissions. In addition, lnCE had a negative correlation with population density (lnPI) (r = −0.181, p < 0.05), and this conclusion aligns with previous research, thus suggesting that compact urban form plays a beneficial role in mitigating carbon emissions within cities. In addition, lnCE showed a positive correlation with land output intensity (lnOI) (r = 0.182, $p < 0.05$), which implies that a higher economic output of land use can promote local carbon emissions.

Table 3. Correlation among variables.

	lnCE	lnPOP	lnPCGDP	lnEC	lnKI	lnLI	lnRI	lnPI	lnOI
lnCE	1								
lnPOP	0.524 ***	1							
lnPCGDP	0.363 ***	0.364 ***	1						
lnEC	0.033	−0.455 ***	−0.654 ***	1					
lnKI	−0.001	−0.037	0.389 ***	−0.332 ***	1				
lnLI	0.123	0.329 ***	0.329 ***	−0.363 ***	0.113	1			
lnRI	0.087	0.494 ***	0.580 ***	−0.748 ***	0.249 **	0.342 ***	1		
lnPI	−0.181 *	0.312 ***	−0.075	−0.374 ***	0.352 ***	0.322 ***	0.355 ***	1	
lnOI	0.182 *	0.497 ***	0.771 ***	−0.775 ***	0.544 ***	0.476 ***	0.702 ***	0.577 ***	1

Note: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$.

The intensive land use indicators yielded significant correlations with each other and the other controlled variables. Within the intensive land use indicator framework, except for labor intensity (lnLI) and capital intensity (lnKI), all the other variables were significantly positively related to each other. R&D investment intensity (lnRI) and lnOI had a high correlation (r = 0.702, $p < 0.001$). lnOI had a medium correlation with lnKI (r = 0.544, $p < 0.001$) and lnPI (r = 0.577, $p < 0.001$).

In terms of the relationship between the intensive land use indicators and the socioeconomic controlled variables, lnKI positively correlated with lnPCGDP (r = 0.389, $p < 0.001$) and negatively correlated with lnEC (r = −0.332, $p < 0.001$). This implies that the better economic condition that cities have, the higher the energy consumption intensity and the lower the capital intensity they tend to own. lnLI showed a positive correlation with both lnPOP (r = 0.329, $p < 0.001$) and lnPCGDP (r = 0.329, $p < 0.001$) and a negative correlation with lnEC (r = −0.363, $p < 0.001$). This indicates that a larger population and higher economic development level come with a higher labor intensity. lnRI showed a positive correlation with lnPOP (r = 0.494, $p < 0.001$), lnPCGDP (r = 0.580, $p < 0.001$), and lnKI (r = 0.249, $p < 0.01$), thus indicating that cities with higher R&D investment intensities tend to have larger populations and higher per capita GDPs.

4.2. OLS Regression Results

After excluding the variables causing severe multicollinearity (VIF > 10), the regression results are shown in Table 4. The regression analysis aimed to explore the relationships between the dependent variable (lnCE) and several independent variables, namely lnPOP, lnPCGDP, lnKI, lnLI, lnRI, and lnPI. Given the heterogeneity among China's cities, the sample was divided into three groups based on per capita GDP: high, middle, and low per capita GDP cities. The results of the regression analysis reveal several significant findings. The variance inflation factor (VIF) values ranged from 1.36 to 2.84, thus suggesting that multicollinearity is not a major concern in the regression model. Population (lnPOP) exhibited a positive and statistically significant relationship with all cities (b = 0.868, $p < 0.001$). This indicates that across all cities, an increase in population is associated with a significant increase in carbon emissions. In high per capita GDP cities, lnPCGDP had a significant positive effect on lnCE (b = 2.260, $p < 0.05$), thus indicating that higher carbon emissions are associated with higher economic development levels in cities with good economic conditions. In low per capita GDP cities, lnKI exhibited a significant positive relationship with lnCE (b = 0.654, $p < 0.05$). In the middle per capita GDP group, lnRI showed a negative and statistically significant association with lnCE (b = −0.409, $p < 0.05$), thus indicating that increases in R&D investment are helpful to reduce urban carbon emissions in the middle development level city group. Finally, lnPI had a negative and statistically significant effect on lnCE in the middle- and low-development level city groups, thus suggesting that a condensed urban population benefits carbon reduction.

Table 4. OLS regression results.

	All Cities	VIF	High per Capita GDP Cites	Middle per Capita GDP Cities	Low per Capita GDP Cities
lnPOP	0.868 ***	1.67	0.531 *	0.987 ***	0.848 ***
	(9.067)		(2.308)	(6.914)	(4.945)
lnPCGDP	0.479	2.84	2.260 *	1.182	−0.651
	(1.874)		(2.039)	(1.114)	(−1.179)
lnKI	0.286	1.82	−0.384	0.554	0.654 *
	(1.748)		(−0.812)	(1.940)	(2.436)
lnLI	0.029	1.36	−0.284	−0.004	0.389
	(0.329)		(−1.430)	(−0.032)	(1.550)
lnRI	−0.285 **	2.15	−0.329	−0.409 *	−0.076
	(−3.332)		(−1.806)	(−2.313)	(−0.559)
lnPI	−1.100 ***	2.22	−0.002	−1.110 *	−1.929 **
	(−3.792)		(−0.004)	(−2.555)	(−3.190)
_cons	8.598 ***		1.117	3.260	12.606 **
	(3.666)		(0.123)	(0.554)	(3.290)
N	153		39	51	63
Adj. R2	0.454		0.349	0.502	0.292

Note: ***, **, and * denote $p < 0.001$, $p < 0.01$, and $p < 0.05$, respectively. t statistics are shown in parentheses. The VIF value is obtained based on the data of all the 153 cities.

4.3. Spatial Regression Results

Using Global Moran's I, this study first tested the spatial autocorrelation hypothesis in this section. Table 5 displays the outcome. The Moran I value was found to be significant at the $p < 0.001$ level and to have positive z score values, thus indicating that the data are spatially clustered. Hence, the GWR model was applied to further explore the relationship between carbon emissions and land use intensity with the consideration of spatial heterogeneity.

Table 5. Spatial autocorrelation results.

Indicator	Value
Moran I	0.213
Z Score	7.418
p Value	0.000

The general performance of the GWR regression model is displayed in Table 6. The adjusted R squared came out to 0.530, which is 16.74% higher than that in the OLS model, thus indicating the better performance of the GWR model. The coefficient in the GWR regression results is spatially visualized in Figure 3. The figure shows obvious spatial distinction. For lnKI, the coefficients are positive in most sample cities except a few cities in northeastern and southern China. The cities in the middle part of China own a high coefficient cluster. For lnKI, most cities showed positive correlation, while the cities in the northeastern China also showed negative impacts. The results of lnRI are very similar to that of lnLI. In terms of lnPI, the results are the opposite. The cities in the northeastern and southern China have a positive correlation, while the coefficients in middle China are negative.

Table 6. Model diagnostics of GWR regression.

Indicator	Value
R2	0.624
Adj. R2	0.530
AICc	320.593
Sigma Squared	0.403
Sigma Squared MLE	0.323
Effective Degrees of Freedom	122.515
Adjusted Critical Value of Pseudo-t Statistics	2.467

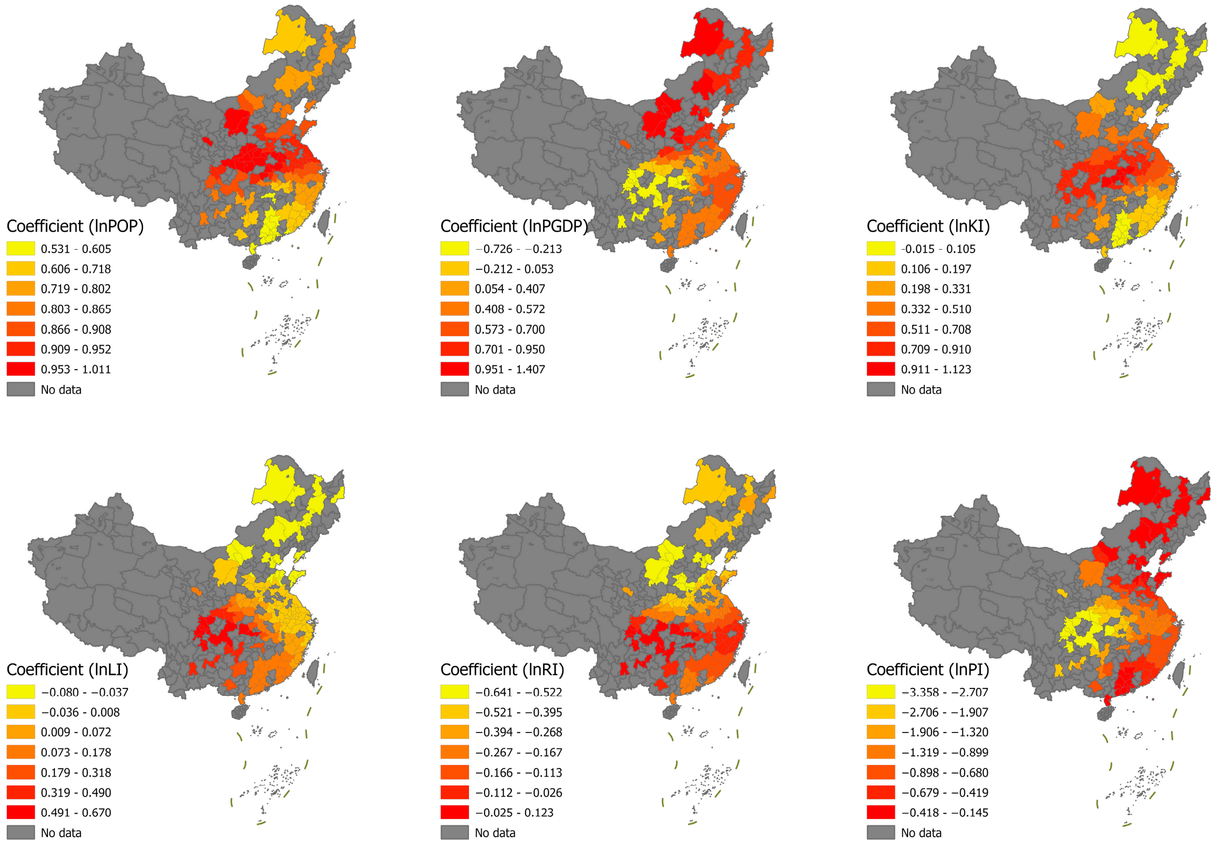

Figure 3. Spatial distribution of coefficient in GWR regression.

5. Discussion

5.1. Policy Implications

In the context of rapid-developing, emerging-market regions, such as in many parts of East Asia, Southeast Asia, the Middle East, Sub-Saharan Africa, and Latin America, the challenges of fast land urbanization, urban sprawl, and extensive land use have become increasingly pronounced. These regions are experiencing rapid economic growth and urbanization, thus leading to significant environmental challenges, including increased carbon emissions and strains on natural resources. Intensive urban land utilization has emerged as a promising strategy to enhance productivity and mitigate these challenges.

Based on the regression results, several implications for carbon emission reduction through intensive land use in rapid-developing regions are discussed as follows: Firstly, it is suggested to adopt differentiated emission reduction policies according to local conditions. One key policy recommendation is to encourage intensive urban land use in high-density areas, particularly in regions with medium and poor economies. This can be achieved through measures such as promoting compact urban development, encouraging the use of public transportation, implementing green building standards, etc.

Another important recommendation is to encourage R&D investment in carbon reduction technologies and practices, particularly in moderately developed regions. By incentivizing research and development in areas such as renewable energy, energy-efficient building materials, and low-carbon transportation, policymakers can help promote innovation and accelerate the transition to a low-carbon economy.

Optimizing fiscal incentive policies, broadening investment, and financing channels can also play a key role in reducing carbon emissions, especially in low-income cities. This can include policies such as tax incentives for companies that invest in renewable energy or energy-efficient technologies, subsidies for energy-efficient building retrofits, and other measures that encourage investment in carbon reduction initiatives.

Overall, by adopting differentiated emission reduction policies that take into account local conditions and by implementing specific measures such as encouraging intensive urban land use, promoting R&D investment, and optimizing fiscal policies, policymakers can help to reduce carbon emissions in rapid-developing regions and promote a more sustainable and livable future for all.

5.2. Limitations and Future Studies

One limitation of this study is that it used cross-sectional data to obtain the primary estimation results. While cross-sectional data can provide valuable insights into the relationship between intensive urban land use and carbon emissions in China's cities, it may not capture the full extent of changes in emissions that occur over time. In particular, the COVID-19 pandemic has caused significant social and economic influence in Asian countries [40]. Future studies would benefit from incorporating time series data and using panel data to better understand the dynamic nature of the relationship between these variables.

Another limitation of this study is that it only examines the linear relationship between intensive urban land use and carbon emissions. However, there are arguments in previous studies that the impact of intensive urban land use on carbon emissions may be nonlinear. For example, some studies suggest that carbon emissions may initially rise and then fall with the level of economic development. As such, it may be important to examine the nonlinear relationships between these variables in future studies to gain a more complete understanding of the relationship between intensive urban land use and carbon emissions in China's cities.

6. Conclusions

Rapid-developing regions are experiencing significant urbanization and expansion, thus resulting in environmental challenges and increased carbon emissions. The impact of intensive urban land use on carbon emissions remains debated. Understanding the implications of intensive urban land use in rapid-developing regions is crucial for developing targeted strategies and interventions to promote sustainable urban development and mitigate environmental impacts. In this paper, we examined the impacts of the main influencing factors on carbon emissions for China's cities based on an extended STIRPAT model with OLS and GWR regression, which incorporated representative intensive urban land use indicators. The main conclusions are as follows.

The findings of this study suggest that intensive urban land use has a significant impact on carbon emissions in China's cities. Specifically, capital intensity, R&D investment intensity, and population density were found to be significant predictors of carbon emissions in middle- and low-income cities. Our results indicate that increasing the capital investment intensity can result in boosts of carbon emissions in low-income cities, with an elasticity of 0.654. R&D investment can significantly reduce carbon emissions in middle-income cities, with an elasticity of -0.409. Moreover, population density can significantly reduce carbon emissions in middle- and low-income cities, with elasticities of -1.110 and -1.929, respectively. Spatial heterogeneity of the effects also exists. Capital intensity, labor intensity, and R&D investment intensity exert positive effects on emissions in middle China and negative influences in northeastern and southern China, whereas population density shows converse spatial effects.

These findings have important implications for policymakers and urban planners in China. The capital investment should shift the focus from emission-intensive industries to green sectors. Increasing R&D investments in carbon reduction technologies and practices can help to accelerate the transition to a low-carbon economy, while promoting compact urban development and encouraging the use of public transportation can help to reduce carbon emissions in densely populated areas. The spatially heterogeneous impacts imply the need for regionally differentiated policies to optimize the emission reduction benefits of land use intensification strategies.

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