Investigating the impact of Urban Form Elements on carbon emissions at Different Development Stages: Based on GWR Models

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Abstract
With rapid urban expansion, cities consume 78% of global energy and are major carbon emitters. Due to uneven urbanisation, Chinese cities at different development stages show varied relationships between urban form and carbon emissions. This study explores the impact of 3D urban form elements on carbon emissions across development stages to promote low-carbon development and carbon neutrality. Using Geographically Weighted Regression (GWR) and Random Forest models, the study analyzed spatial heterogeneity and non-linear relationships. Key steps included classifying city development stages, estimating city-level emissions using inventories and Night Time Light data, and examining spatial autocorrelation. Results indicate that factors such as building height and built-up area have a significant impact on emissions. These findings provide targeted recommendations for carbon reduction and sustainable urban development

Keywords: Carbon emissions, Urban development Levels, Urban forms, Geographically Weighted Regression Model

Introduction

Carbon emissions have impacted global climate change, leading to a rise in global average temperature, causing extreme weather events to become more frequent, and affecting human production and life(n.d.). With the gradual advancement of global urbanisation, cities are the most vulnerable to climate change and major contributors to it. According to statistics from UN-Habitat, cities consume 78% of the world's energy, and more than 60% of greenhouse gas emissions come from urban areas(Xia et al., 2020). To address this issue, the international community has proposed the Sustainable Development Goals, the United Nations Framework Convention on Climate Change, and the Special Report on Global Warming of 1.5ºC. As the world's largest carbon-emitting country, China has also actively participated in carbon reduction and control actions, proposing the goals of peaking carbon emissions by 2030 and achieving carbon neutrality by 2060 based on its national circumstances.

China's urbanisation process is rapid. According to data from the National Bureau of Statistics, the urbanisation rate in China was 65.22% by the end of 2022, with the urbanisation rate in nine provinces exceeding 70%. Previous studies have shown that the optimisation of urban spatial form plays a significant role in reducing carbon dioxide emissions(Xia et al., 2020). Urban form is generally considered the spatial arrangement and organisational pattern of human activities, affecting land use structure, resource utilisation efficiency, transportation configuration, infrastructure construction, and even the urban heat island effect(Liang et al., 2020). Numerous studies demonstrate that urban form is closely related to urban CO_2 emission levels(2012; Xia et al., 2020; Zuo et al., 2020).

Traditional studies mainly focus on analyzing the impact of two-dimensional urban form indicators on urban carbon emissions. For instance, Ou et al. found that the fragmentation pattern of urban land leads to increased CO_2 emissions across all city levels(J. Ou et al., 2019). Yasuyo Makido et al. studied the relationship between CO_2 emissions and urban form in Japanese urban areas(Makido et al., 2012), while Fragkias et al. pointed out that during rapid urbanisation, population growth and resource consumption lead to the expansion of urban form, which significantly contributes to the increase in CO_2 emissions("Investigating the differentiated impacts of socioeconomic factors and urban forms on CO2 emissions: Empirical evidence from Chinese cities of different developmental levels - ScienceDirect," n.d.). However, with high-density cities becoming an important goal for global carbon reduction and control, three-dimensional urban form indicators can better reveal the vertical spatial development and built environment of high-density cities as compared to traditional two-dimensional urban form indicators(Lin et al., 2021; Tian et al., 2024; Wang et al., 2025). Therefore, it is necessary to analyze the impact of the three-dimensional built environment on urban carbon emissions to promote green and low-carbon development models.

At the same time, due to the varying urbanisation progress across Chinese cities, there are significant differences in the socio-economic development, energy consumption structures, and carbon dioxide emission patterns among different cities(Ou J. et al., 2019). Additionally, urban spatial morphology elements, such as the scope of built-up areas, land use structures, urban compactness, and urban spatial forms, also show considerable variation. However, how the differences in urban development levels influence the relationship between urban morphology and CO_2 emissions has not been thoroughly explored in the current literature. Taking Chinese cities as an example, most studies investigating the impact of urban morphology on CO_2 emissions focus on megacities while neglecting underdeveloped and low-income cities. Although it is well-known that there are substantial disparities in carbon dioxide emissions across cities with different development levels(Behera and Dash, 2017; Wang et al., 2018), existing studies lack sufficient evidence to explain the differential impacts of multidimensional characteristics of urban morphology on carbon emissions. Furthermore, they do not clarify whether compact development models have universal emission reduction effects across cities with varying economic levels in China. Given this, there is an urgent need to construct a systematic research framework to explore the differentiated mechanisms through which urban spatial structures affect carbon emission intensity, while incorporating the dynamic characteristics of urban development stages for comprehensive analysis(Ou J. et al., 2019).

This study analyses the carbon emission characteristics of cities at different developmental stages based on their three-dimensional spatial form and explores targeted sustainable development models. Cities are first classified by development levels, and a carbon emission dataset derived from energy consumption and nighttime light data is used to calculate annual city-scale emissions. Key three-dimensional urban morphological metrics are then summarized and analysed. Geographically Weighted Regression (GWR) is applied to quantify the spatial heterogeneity of CO∆emissions in relation to urban morphology and socioeconomic factors. The Ordinary Least Squares (OLS) regression model identifies global driving factors of city-level CO∆emissions, while the GWR model reveals local variations by providing unique parameters for each observation. This approach uncovers the spatial characteristics and carbon emission patterns of cities, offering insights into sustainable urban development models and valuable references for policymakers.

Date and methodology

Study areas

This study examines prefecture-level and above cities in mainland China, focusing on the impact of industrialisation and urbanisation since the reform and opening-up policy. From 2000 to 2016, China's GDP increased sevenfold to 74.4 trillion yuan, accompanied by rising energy consumption and greenhouse gas emissions. China accounts for 23.0% of global energy consumption and 27.3% of carbon emissions, making it the largest emitter(Shi et al., 2018). Due to regional resource endowment, industrial structure, and energy efficiency, cities show significant spatial differences in carbon emission trajectories. Identifying the dynamic evolution of carbon emission drivers is crucial for creating differentiated emission reduction strategies that consider regional heterogeneity and sustainable development.

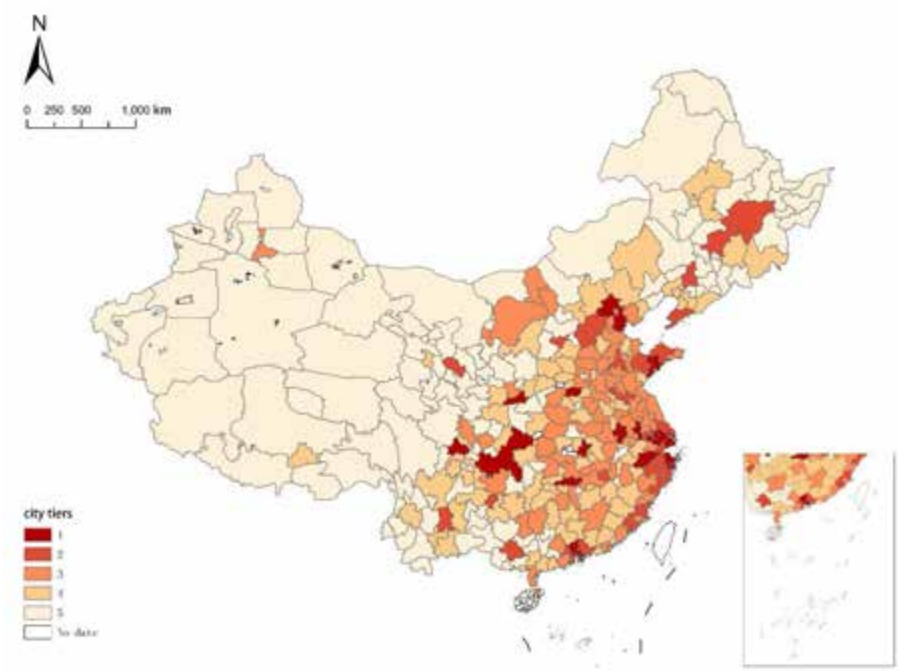

Figure 1 The geographical distribution of five-tier cities in mainland China.

The traditional classification of cities primarily relies on indicators such as built-up area size, city GDP, urban population, and population density. To evaluate the impact of socioeconomic factors and urban morphology on carbon dioxide emissions while considering differences in development levels, this study adopts the city classification system published by China Business Network (CBN) in 2024, which categorises Chinese cities into five tiers: first-tier, second-tier, third-tier, fourth-tier, and fifth-tier cities.

These metrics are sourced from commercial and internet data, reflecting various aspects such as the level of economic development, household consumption ability, local fiscal income, education level, educational resource level, and urban infrastructure quality. Subsequently, a comprehensive commercial development index for each city is calculated through principal component analysis and a weighted scoring method(Bai et al., 2018).

As shown in Figure 1, according to the 2024 rankings of the index, there are 19 first-tier cities, 30 second-tier cities, 70 third-tier cities, 90 fourth-tier cities, and 128 fifth-tier cities in China in 2024. The first-tier cities are, in order: Beijing, Shanghai, Shenzhen, Guangzhou, Chengdu, Hangzhou, Chongqing, Suzhou, Wuhan, Xi'an, Nanjing, Changsha, Tianjin, Zhengzhou, Dongguan, Wuxi, Ningbo, Qingdao, and Hefei.

Data sources

City-level CO2 emissions

Generally speaking, carbon dioxide emission data originate from energy statistics based on standard IPCC methods(Castles and Henderson, 2003; Li et al., 2021). The current national statistical system exhibits a clear hierarchical attenuation characteristic in energy data: energy consumption data released by the National Bureau of Statistics is mostly focused on the macro level, and there are significant data gaps at the prefecture-level (particularly in central and western cities).

To address the lack of urban-scale energy statistical data, a substantial amount of work has been successfully conducted to estimate urban-scale CO2 emissions based on nighttime light imagery. Nighttime light imagery has been proven to be a potential data source for estimating CO2 emissions, as it can detect artificial light associated with human activities.

In terms of carbon emission calculations, this study utilises the carbon emission gridded data for months 1-12 from the ODIAC 2023 dataset. The primary sources of this dataset are statistical data from fields such as energy consumption and industrial production. This dataset is pioneering in its use of nighttime light data combined with emission/location profiles of individual power plants to estimate the global spatial distribution of fossil fuel CO_2 emissions. Through an innovative emission modeling approach, it has achieved a 1x1 kilometer resolution data product for global fossil fuel CO_2 emissions.

This study processed the outliers of carbon emissions as 0 and greater than 10,000 in the dataset, summed up the annual carbon emissions for 2023 within the urban areas of each prefecture-level city, and assigned the results to each city boundary to obtain the annual carbon emissions within the city boundary. The formulas are as follows:

$$E_{i,j}^{annual} = \sum_{m=1}^{12} E_{i,j}^{(m)}$$

$$E_k^{total} = \sum_{(i,j)\in A_k} E_{i,j}^{annual} \times A_{i,j}^{k}$$

where $E_{(i,j)}^{annual}$ represents the annual carbon emissions of grid cell (i,j) in 2023. E_k^{total} represents the total carbon emissions within the city boundary k in 2023. $A_{(i,j)}^{k}$ represents the area proportion of grid cell (i,j) within the built-up area of city k.

Comprehensive Indicators of Socioeconomic Development and Urban Form

This study selected two types of indicators related to socioeconomic development and urban morphology to analyse their impact on CO_2 emissions. The first type includes socioeconomic variables such as GDP and population density, which are often used to represent economic performance and population scale; thus, they are important factors influencing changes in urban CO_2 emissions. This study utilised GDP data, population data, and population density data of various cities. GDP data for 2023 of each city and the corresponding GDP data for the Primary Industry, Secondary Industry, and Tertiary Industry were obtained from the "China Urban Statistical Yearbook" and some city statistical yearbooks. For data consistency, some cities without statistical data were excluded from this analysis. Additionally, spatial distribution raster data of China's population at 1km resolution for 2023 were obtained from the LnadScan platform. Outliers were processed during usage, and population density within each city in 2022 was derived by summing the raster data.

The second type is the urban morphology indicator. Urban morphology can influence economic functions and efficiency, produce social impacts within urban environments, and ultimately affect the design and regulation of urban spatial uses(Fang et al., 2015).

Based on previous studies(Biljecki and Chow, 2022; Chen et al., 2025; Fang et al., 2015), this paper selects the following indicators to represent urban morphological characteristics: Total Area of Urban Built-up Area (TA), Average Building Height (ABH), Shape Index of Urban Built-up Area (SI). Transportation and urban expansion also have significant impacts on CO_2 emissions(Lopez-Aparicio et al., 2025; Wu et al., 2022). This paper selects Road Density (RD) to represent the transportation characteristics within urban morphology.

Table 1 summarises the calculation formulas and units of the aforementioned indicators. To facilitate subsequent analysis, these variables are subjected to Z-score standardisation to eliminate the effects of dimensionality and outliers.

Research steps

Spatial autocorrelation

Moran's I index is an important tool for evaluating spatial autocorrelation, used to measure the dependency and heterogeneity characteristics among spatial objects. From a spatial scale perspective, Global Moran's I describes the overall degree of spatial association, while Local Moran's I reflects the similarity and differences among local spatial units(Wang et al., 2023). Both range from [-1,1], with positive values indicating similarity among spatial units and negative values indicating differences.

In statistical testing, z-scores and p-values are used to assess the strength of correlation and its significance.

Table 1 Detailed information on the indicators used in this study

Indicator	Calculation Formula/Definition	Unit
PD (Population density)	P_i represents the population of grid i; i represents the area of grid i.	People/km²
IS (Proportion of secondary industry)	The proportion of the secondary industry (e.g., industry, construction, etc.) in the gross domestic product (GDP).	%
RD(Road density)	L_d represents the total road length; represents the total area of the district	km/km²
TA (Total Area of Urban Built-up Area)	Area of developed and constructed zones within the city	km²
BH (Building height)	$H_{avg} = \frac{\sum_{i=1}^{n} h_i \cdot A_i}{\sum_{i=1}^{n} A_i}$ A_i represents the building height of grid i; A_i represents the area of grid i.	m
SI (Shape index)	P represents the perimeter of the built-up area, A represents the area of the built-up area	/

In spatial clustering analysis, the global mean and local mean are key parameters. A local mean higher than the global mean forms a high-high (HH) cluster, while a local mean lower than the global mean forms a low-low (LL) cluster. Observed values higher than the local mean form a high-low (HL) cluster, while those lower than the local mean form a low-high (LH) cluster(Su et al., 2014). These cluster types are distributed in four quadrants in the Moran scatterplot, corresponding to the central trend of regression models.

The geographically weighted regression model

The Geographically Weighted Regression Model (GWR) is a local spatial technique that can be used to examine the spatial variability of regression parameters and model performance. Relationships in geographic space often vary due to differences in geographic locations. Compared to general models, while classical Ordinary Least Squares (OLS) regression is a simple linear regression, its coefficients reflect the generalised relationships within the study area but do not account for the spatial components behind these effects. The introduction of the GWR model allows regression coefficients to change with spatial location by fitting a local regression model at each geographic location, thereby better explaining spatial heterogeneity.

The GWR model can be regarded as a spatial decomposition extension of the general linear regression model. The form is as follows:

$$y_i = \beta_0(\mu_i, \nu_i) + \sum_{i=1}^{k} x_{ij}\beta_j(\mu_i, \nu_i) + \varepsilon_i, \qquad (i = 1,2,\ldots,m, j = 1,2,\ldots,k)$$

where Δis the error term satisfying the spherical disturbance assumption; Δ_0 (μ_i,Δ_i) is the intercept term; k represents the number of factors, and i represents the i-th city.
Δ_j (μ_i,Δ_i) is the local regression parameter to be estimated at the regression point (μ_i,Δ_i), representing the latitude and longitude coordinates of the i-th city.

Results

The spatial features of city-level CO2 emissions

Based on the aforementioned methods, due to defects in CO2 emission data in some cities, this study estimates the 2023 CO2 emissions of 371 cities in China, as shown in Figure 2. The total CO2 emissions of Chinese cities amount to approximately 12.6 billion tons. About 249 cities have carbon emissions below the average (33.9 million tons). It can be observed that cities with relatively high CO2 emissions are mostly concentrated in the Yangtze River Delta (YRD), the Pearl River Delta (PRD), the Beijing-Tianjin-Hebei region (BTH), the Chengdu-Chongqing economic circle, and the northeastern regions of China, such as Changchun and Harbin.

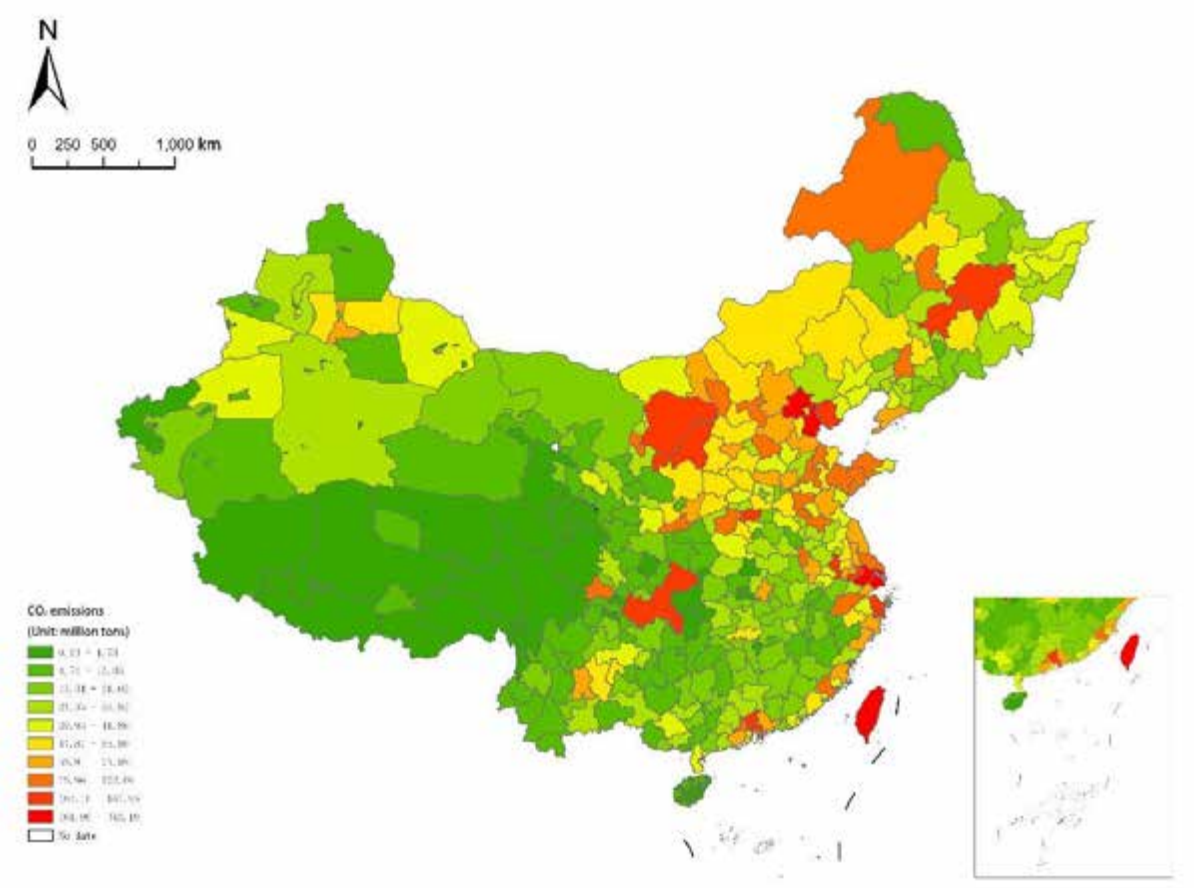

Figure 2 China's City-Level CO2 Emissions in 2023 (Million Tons)

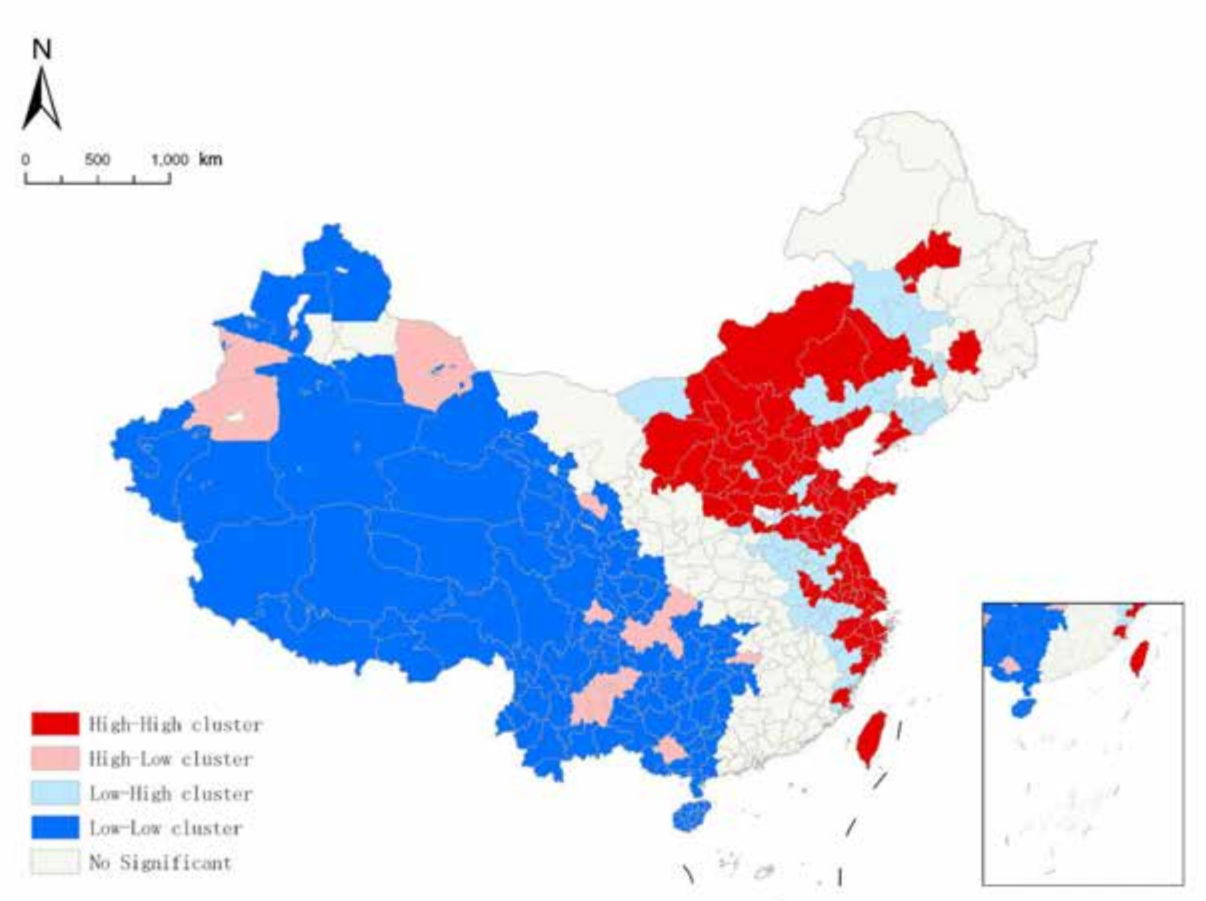

Figure 3 Local Moran's I clusters of CO2 emissions of Chinese cities

The spatial distribution of such CO2 emissions is closely related to regional development patterns. Among the top 10 cities with the highest carbon dioxide emissions, 7 are first-tier cities. These cities with higher carbon dioxide emissions benefit from favourable geographic locations or policy advantages, resulting in faster urbanisation, larger populations, more developed economies, and more intensive industries compared to other cities, particularly in the YRD, PRD, and BTH regions. In contrast, the northeastern region of China, which was once the heavy industrial base of the country, is currently undergoing policy initiatives aimed at addressing population loss in the area.

Cities with lower carbon dioxide emissions are typically located in less developed regions, including southern, northwestern, western, and parts of central China. Among these, the central region has historically sustained a large population, mostly consisting of second-tier and third-tier cities. In contrast, the western region, due to factors such as geographical conditions, has developed at a relatively slower pace. Although it occupies over 70% of China's territory, it accounts for only 30% of the population, with low urbanisation rates and slower economic development, mostly consisting of fourth-tier and fifth-tier cities.

This study calculates the global Moran's I to assess the spatial clustering of city-level CO2 emissions in China. It finds that the global Moran's I of CO2 emissions is 0.17 ($p < 0.01$), indicating a significant positive spatial autocorrelation of CO2 emissions. To further analyse the spatial characteristics of city-level CO2 emissions in China, this study employs the local Moran's I.

The CO2 emission LISA map shown in Figure 3 geographically depicts the local spatial correlation of CO2 emissions. HH clusters are mainly concentrated in YRD, BTH, parts of the Shandong Peninsula, and a few northeastern cities in China, which are densely populated and economically developed. LL clusters are primarily distributed in the northwestern and southwestern regions of China, involving some cities in the central region. HL clusters are relatively dispersed, mainly distributed in the Xinjiang region of northwestern China, the Chengdu-Chongqing region of southwestern China, parts of Shanxi, Guizhou, and Guangxi, and form a relatively continuous concentration in Yunnan. LH clusters are mainly distributed around HH clusters. A particularly notable aspect is that HH clusters do not appear in the PRD region, which features a developed and prosperous economy and a high level of urbanisation. One possible reason for this could be the impact of CO_2 emissions from surrounding cities.

Major factors influencing city-level CO_2 emissions

To comprehensively understand the driving factors and effects behind city-level carbon dioxide emissions, this paper first uses the OLS model to detect the impact of eight explanatory variables on urban CO_2 emissions. The Z-score standardisation is performed on these explanatory variables to eliminate the effects of dimensions and outliers. The ANOVA F-test shows that the overall model has statistical significance ($p < 0.001$), and the adjusted R-squared value (0.79) indicates a relatively high goodness of fit.

There is no issue of multicollinearity, as all variance inflation factors (VIF) reported for the variables are far below 10.

The results are presented in Table 2. The coefficients indicate that most explanatory variables are positively correlated with CO_2 emissions, particularly the area of developed land, building height, and significantly contribute to urban CO_2 emissions. PD and IS promote urban CO_2 emissions, while RD has a significant effect on reducing urban CO_2 emissions, and SI has a minimal impact.

Table 2 OLS analysis results

	Coefficient	Std. Error	T value	Pr.(>|t|)	VIF
Constant	38.5688	1.3974	27.5999	0.0000*	
PD	9.0387	5.6237	1.6072	0.1093	3.9287
IS	-10.1902	2.3048	-4.4212	0.0000*	3.5577
RD	17.5675	1.9847	8.8516	0.0000*	2.6662
TA	27.9687	3.0078	9.2986	0.0000*	5.7252
BH	0.7631	2.0443	0.3733	0.7093	2.7712
SI	9.1118	1.4244	6.3968	0.0000*	1.1014

As mentioned above, the global regression model assumes that the relationship between CO_2 emissions and each explanatory variable is the same across all locations, and the results of this model fail to explain the local heterogeneity of driving factors. Therefore, the GWR model in this paper is set with the same variables. The spatially distributed local R-squared values described in Figure 4 also indicate that the comprehensive statistical effects of our explanatory variables on CO_2 emissions vary between 0.702 and 0.925 among Chinese cities.

As shown in the figure, the local R-squared values roughly exhibit a ring-shaped distribution, gradually decreasing from the eastern coastal areas. The R-squared values of the GWR model for the vast majority of studied cities are higher than those of the global regression model, with only some cities in the southwestern region, parts of the central region, and parts of the northwestern region falling below the OLS threshold (0.79).

The results indicate that the range of regression coefficients relative to their standard deviations is quite broad, with the minimum value (road network density) being -8.749 and the maximum value (built-up area) being 22.438. The greater the range of variable coefficients, the greater the spatial variation in the contribution and influence of the factors, which demonstrates the appropriateness of the GWR model in providing better explanations for local estimates.

To further explore the spatial heterogeneity in the relationship between each explanatory variable and CO_2 emissions, we generated maps representing the spatial distribution of coefficients for each factor (Figure 5). Consistent with the OLS model, the average building height, built-up area, and secondary industry GDP of cities were shown to have a positive impact on CO_2 emissions in the studied cities, but their relationships with CO_2 emissions varied spatially.

Meanwhile, other factors exerted bidirectional influences on cities' CO2 emissions, with certain differences observed among different cities—an aspect not revealed by the global regression model.

Research and development, in all the studied cities, TA is a key driver of urban CO2 emissions, maintaining a still significant coefficient. Among socio-economic indicators, the regions most affected by IS are concentrated in the eastern coastal area, the northeast region, some central cities, and some cities in the northwest. In terms of urban development levels, in some Tier 1 cities located in the eastern coastal areas, CO2 emissions are still influenced by IS. Relatively speaking, the influence degree in Tier 1 cities in the Chengdu-Chongqing area, PRD, and BTH region is smaller compared to other Tier 1 cities. This is mainly because Tier 1 cities like Beijing, with urbanisation progress and economic structure upgrades, have gradually transferred high-energy-consuming and high-pollution industries to surrounding areas (such as Hebei Province, Jiangsu Province, etc.). They have also implemented stricter environmental protection policies and carbon emission control measures.

The secondary industry in Tier 2 and Tier 3 cities overall has a significant impact on carbon emissions. This is because the economic development of Tier 2 and Tier 3 cities still primarily relies on the secondary industry, especially traditional industries with high energy consumption and high pollution (such as steel, chemical industry, cement, coal, etc.), which have high energy consumption and carbon emission intensity. At the same time, due to the division of labor in regional economies, much of the secondary industry eliminated by Tier 1 cities has shifted to Tier 2 and Tier 3 cities due to factors like costs, labor, and policies. Additionally, some Tier 2 and Tier 3 cities are resource-based cities (e.g., those rich in coal, oil, and minerals), and their economic development is highly dependent on resource extraction and processing, activities that are typically accompanied by high carbon emissions.

Interestingly, in the southwestern regions such as Yunnan, Guizhou, Guangxi, and parts of Shandong's cities, the secondary industry has a relatively small impact on urban carbon dioxide emissions. These cities are mostly Tier 4 and Tier 5 cities, with slow urbanisation processes, and some are just beginning to develop. Additionally, influenced by geographical and natural conditions, Sichuan, Yunnan, Guizhou, and Guangxi possess abundant water resources. Hydropower occupies a significant proportion in their energy structure, making them key provinces for clean energy output. Moreover, in recent years, due to low-carbon policies and eco-priority strategies, the country has implemented strict ecological protection policies in these regions, emphasizing the introduction of energy-saving and emission-reduction technologies. All these factors have resulted in the secondary industry having a minimal impact on urban carbon dioxide emissions in these cities.

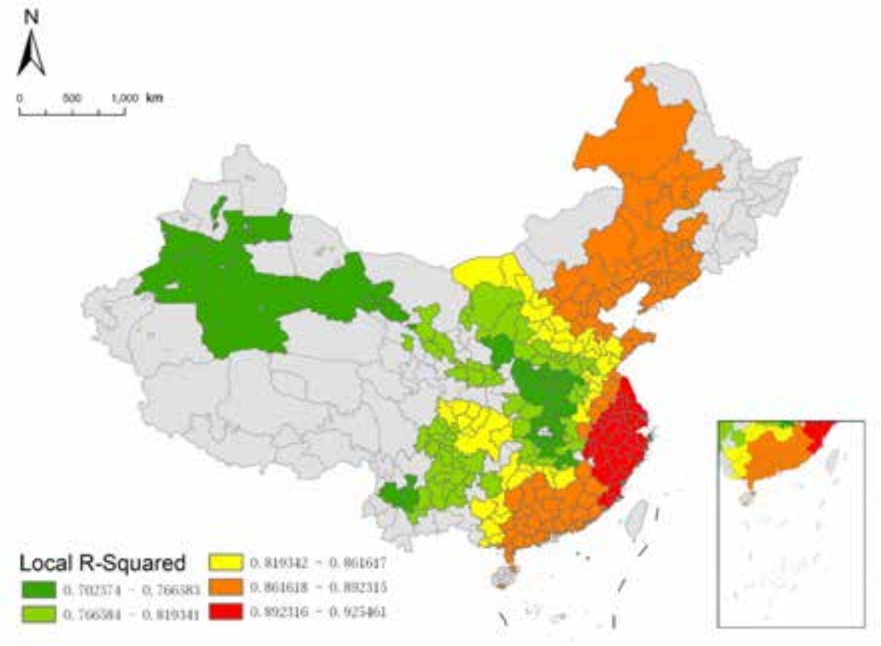

Figure 4 The spatial distribution of R-squared values from the GWR model.

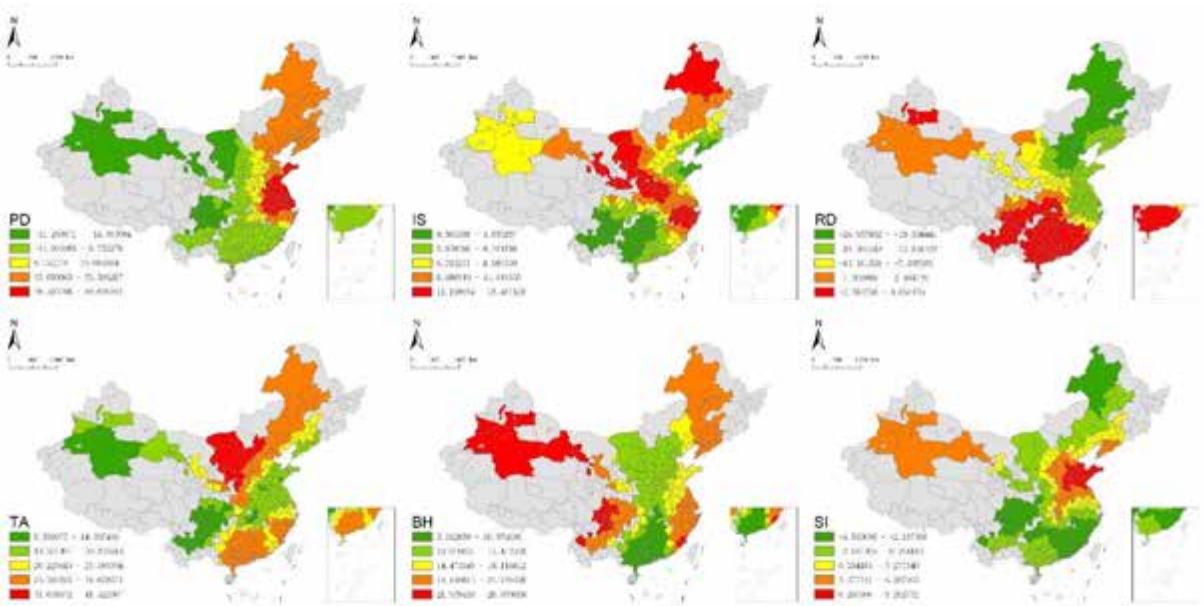

Figure 5 Spatial distribution of GWR local coefficient

Moreover, the study also found that PD has a bidirectional impact on urban CO2 emissions, generally showing a positive effect in the eastern and northern regions, while exhibiting a negative effect in the western, southwestern, and certain southern coastal regions. China's Tier 1 and Tier 2 cities are extensively distributed in areas such as the YRD and BTH regions. These areas are characterised by a generally high level of urbanisation and developed economies, which strongly attract populations, leading to significant migration to these regions. High population density implies more residential, transportation, commercial, and industrial activities, which directly result in increased energy consumption, thereby driving the rise in CO2 emissions. At the same time, high population density is usually accompanied by increased traffic pressures. Although the public transport systems in the YRD region are relatively well-developed, with further increases in population density, the use of private cars remains quite common, which can lead to traffic congestion and increased vehicle emissions, further driving up CO2 emissions.

In the central and western regions, most cities are Tier 3, Tier 4, or Tier 5 cities. These lower-level cities exhibit lower economic activity and energy consumption intensity, wherein an increase in population density actually enhances resource utilisation efficiency and reduces per capita carbon emissions. At the same time, due to their lower economic levels, cities with low development levels have limited demand for urban expansion and large-scale infrastructure construction. Compared to cities with high development levels, an increase in population density does not lead to large-scale construction activities that result in increased carbon emissions.

In the indicators of urban morphology, research has found that both BH and TA positively influence urban CO2 emissions. The impact of BH on urban CO2 emissions shows a trend of being high in the eastern coastal and western regions and low in the central region. The impact of TA on urban CO2 emissions exhibits a trend of being high in the southeastern coastal and northern regions, while relatively low in the northern coastal, southwestern, and northwestern regions.

The eastern coastal region is the core area of China's economy and industrialisation, featuring a rapid urbanisation process. Over the years of urbanisation, this has resulted in large urban built-up areas and generally taller building heights, gradually transforming into high-density cities. Greater building heights often indicate higher energy consumption, such as for elevator operation, air conditioning systems, as well as increased heating and lighting demands, leading to higher CO2 emissions. At the same time, due to greater ventilation, lighting, and cooling demands, high-rise buildings typically consume more energy per unit area than low-rise buildings, further exacerbating carbon emissions.

Additionally, eastern coastal cities concentrate a large amount of industry and services, with high population and economic activity densities. In the course of urbanisation, city expansion is required to accommodate significant population influxes, generally accompanied by substantial infrastructure construction, industrial activities, and transportation, all of which are major sources of CO2 emissions.

In the central and parts of western regions, Tier 2 and Tier 3 cities account for a large proportion. In recent years, rapid urbanisation and economic development have shown strong growth potential. Through policy support (such as the Western Development strategy), the urbanisation process has been accelerated in recent years. Some central cities (such as Chengdu, Chongqing, and Xi'an) are undergoing rapid growth, with the expansion of built-up areas and an increasing number of high-rise buildings. The energy consumption patterns of these buildings resemble those of the eastern coastal regions, resulting in building height having a significant impact on carbon emissions. In regions such as Yunnan, Guizhou, and Guangxi, where there are a larger number of Tier 4 and Tier 5 cities, most cities exhibit lower levels of urbanisation. The expansion of built-up areas is more evident in low-density urban development, with lower intensity in economic activities and energy consumption, thereby making the impact of built-up area size on CO2 emissions relatively small. In the northwestern regions (such as Xinjiang and Gansu), although the built-up area size has expanded somewhat, the low population density, relatively simplistic urban functionality, and industrialisation and economic activities concentrated in a few sectors (such as resource extraction) result in the built-up area size having a weaker impact on overall CO2 emissions.

The influence of RD on urban CO2 emissions is mainly negative, with only a few areas showing a positive impact (mostly in the PRD region). In northern regions, an increase in road density significantly reduces urban CO2 emissions, as these regions originally have low road density, potentially causing insufficient transportation networks, vehicle detours, and traffic congestion. High road density enhances connectivity within cities, providing residents with more travel options, shortening commuting distances, and reducing overall traffic carbon emissions. In contrast, the generally higher road density in the southern regions results in relatively smaller reductions in urban CO2 emissions with increased density. Additionally, the high road density in the Pearl River Delta region contributes to an increase in urban CO2 emissions. On the whole, cities at all development levels still need to further improve their road density, which aligns with the national requirement for road density to exceed 8km/km2.

Research findings indicate that SI factor also exhibits a bidirectional effect. In urban built-up areas of cities located in the northern coastal region, certain eastern coastal areas, parts of central regions, and specific regions of Xinjiang, an increase in the shape index of urban built-up areas leads to an increase in urban CO2 emissions, while an increase in the shape index in neighboring areas results in a reduction in urban CO2 emissions. This is because the irregular shape of urban built-up areas in these regions leads to increased transportation demand, thereby raising carbon emissions.

Discussion and Conclusion

Numerous studies have examined the driving factors of CO2 emissions, most of which rely on traditional regression models. These models fail to reveal spatial variations in these impacts, thereby overlooking the fact that due to differences in conditions and development statuses of these locations, the effects of factors may vary between different places. This study adopts a GWR model, which, instead of generating a single set of model parameters for the entire study subject, enables us to identify local variations in statistical relationships, where closer observations have a greater influence on the parameters than more distant ones.

Under the support of traditional regression models and geographically weighted regression models, we compared the coefficients of each driving factor globally and locally. The traditional ordinary least squares model shows that built-up area and building height are the main factors promoting CO2 emissions, while road network density negatively correlates with CO2 emissions. The remaining factors do not play a significant role in influencing CO2 emissions. Moreover, our geographically weighted regression model shows that the impact of these remaining factors varies spatially. Built-up area and building height still maintain a consistent positive correlation with urban CO2 emissions.

It is worth noting that the geographically weighted regression model used in the study also provides many important results not revealed by the ordinary least squares model, such as the bidirectional influence relationship between factors like population density and shape index with urban CO2 emissions. For Tier 1 cities, most of the CO2 emissions are greatly influenced by factors like building height and built-up area, while being less influenced by secondary industry and shape index. Tier 2 and Tier 3 cities are greatly influenced by built-up area and also by secondary industry, building height, and road network density but are less influenced by other factors. Tier 4 and Tier 5 cities are significantly influenced by secondary industry and built-up areas.

In the eastern and central-western regions (e.g., Zhejiang, Henan, Hubei, Gansu, etc.), due to the dominance of traditional high-energy-consuming industries or high industrial aggregation, the secondary industry has a significant impact on carbon emissions. In contrast, coastal regions (e.g., the Pearl River Delta, Beijing-Tianjin-Hebei) and some Tier 1 cities (e.g., Beijing) experience a smaller impact due to industrial upgrading, relocation of high-energy-consuming industries, and strict carbon emission control policies. Population density exhibits a bidirectional impact on carbon emissions; in the eastern coastal areas, due to their strong economic attractiveness, increased habitation, transportation, commercial, and industrial activities lead to higher energy consumption. The impact of road density varies regionally; an increase in road density reduces carbon emissions in the northern regions, while in some cities of the Pearl River Delta, excessive road density increases carbon emissions. Building height and built-up area have a significant positive impact on carbon emissions, with building height having a greater influence in the eastern and western regions and a smaller impact in the central region. The built-up area has a higher impact in the southeastern coast and northern region and a lower impact in the central and northwestern regions. The shape index of built-up areas positively affects carbon emissions in the eastern and northern regions, whereas in other regions, the shape index factor reduces carbon emissions.

The advent of climate change has drawn global attention to how urban carbon dioxide emissions can be reduced. From this perspective, China's rapid development not only threatens the country's sustainable development but also impacts future climate change. However, due to varying levels of urban development and differing processes of urbanisation, it is crucial to study how disparities in urban development levels affect the relationship between urban morphology and CO2 emissions.

Despite our research findings demonstrating the increasing trend of carbon dioxide emissions, economic development remains a prerequisite for the vast majority of cities in China. However, cities at different stages of development can make industrial layout choices based on their respective carbon emission characteristics. Additionally, renewable energy sources such as wind and tidal energy can be introduced, or cities can continue developing advantageous renewable energy industries according to natural conditions. For example, cities in Sichuan and Yunnan can further develop hydropower. Policies related to population also need to be improved by controlling the population size in economically developed cities along the southeast coast and directing labor migration toward cities in the western and northeastern parts of the country. Suitable urban built-up area intensity development should be undertaken according to city rank and population density, controlling building heights and road network density to achieve compact urban development or appropriately expanding urban built-up areas to advance urbanisation processes. China undoubtedly faces significant challenges in reducing and maintaining carbon dioxide emissions according to internationally recognised standards; we hope our research contributes to this endeavor to some extent.

References

Bai, H., Wang, J., Zeng, A.Z., 2018. Exploring Chinese consumers' attitude and behavior toward smartphone recycling. Journal of Cleaner Production 188, 227–236.

Behera, S.R., Dash, D.P., 2017. The effect of urbanization, energy consumption, and foreign direct investment on the carbon dioxide emission in the SSEA (South and Southeast Asian) region. Renewable and Sustainable Energy Reviews 70, 96–106.

Biljecki, F., Chow, Y.S., 2022. Global Building Morphology Indicators. Computers, Environment and Urban Systems 95, 101809.

Castles, I., Henderson, D., 2003. The IPCC Emission Scenarios: An Economic-Statistical Critique. Energy & Environment.
Chen, D., Feng, Y., Li, X., Qu, M., Luo, P., Meng, L., 2025. Interpreting core forms of urban morphology linked to urban functions with explainable graph neural network. Computers, Environment and Urban Systems 118, 102267.

Fang, C., Wang, S., Li, G., 2015. Changing urban forms and carbon dioxide emissions in China: A case study of 30 provincial capital cities. Applied Energy 158, 519–531.

Global and regional drivers of accelerating CO2 emissions [WWW Document], n.d.

Investigating the differentiated impacts of socioeconomic factors and urban forms on CO2 emissions: Empirical evidence from Chinese cities of different developmental levels - ScienceDirect [WWW Document], n.d. URL .

Li, Q., Gao, M., Li, J., 2021. Carbon emissions inventory of farm size pig husbandry combining Manure-DNDC model and IPCC coefficient methodology. Journal of Cleaner Production 320, 128854.

Liang, Z., Wu, S., Wang, Y., Wei, F., Huang, J., Shen, J., Li, S., 2020. The relationship between urban form and heat island intensity along the urban development gradients. Science of The Total Environment 708, 135011.

Lin, J., Lu, S., He, X., Wang, F., 2021. Analyzing the impact of three-dimensional building structure on CO2 emissions based on random forest regression. Energy 236, 121502.

Lopez-Aparicio, S., Grythe, H., Drabicki, A., Chwastek, K., Toboła, K., Górska-Niemas, L., Kierpiec, U., Markelj, M., Strużewska, J., Kud, B., Sousa Santos, G., 2025. Environmental sustainability of urban expansion: Implications for transport emissions, air pollution, and city growth. Environment International 196, 109310.

Makido, Y., Dhakal, S., Yamagata, Y., 2012. Relationship between urban form and CO2 emissions: Evidence from fifty Japanese cities. Urban Climate 2, 55–67.

Ou, J., Liu, X., Wang, S., Xie, R., Li, X., 2019. Investigating the differentiated impacts of socioeconomic factors and urban forms on CO2 emissions: Empirical evidence from Chinese cities of different developmental levels. Journal of Cleaner Production 226, 601–614.

Ou J., Liu X., Wang S., Xie R., Li X., 2019. Investigating the differentiated impacts of socioeconomic factors and urban forms on CO2 emissions: Empirical evidence from Chinese cities of different developmental levels. Journal of Cleaner Production 226, 601–614.

Shi, X., Li, W., Wu, H., Guo, W., Ye, C., Liao, W., Huang, Y., 2018. Camellia psilocarpa (Theaceae), a new species from Guangdong, China, based on morphological and molecular data. Phytotaxa 338, 209–215.

Su, Y., Chen, X., Li, Y., Liao, J., Ye, Y., Zhang, H., Huang, N., Kuang, Y., 2014. China∆s 19-year city-level carbon emissions of energy consumptions, driving forces and regionalized mitigation guidelines. Renewable and Sustainable Energy Reviews 35, 231–243.

Tian, P., Cai, M., Sun, Z., Liu, S., Wu, H., Liu, L., Peng, Z., 2024. Effects of 3D urban morphology on CO2 emissions using machine learning: Towards spatially tailored low-carbon strategies in Central Wuhan, China. Urban Climate 57, 102122.

Wang, G., Li, M., Li, Y., Chen, T., Heng, C.K., 2025. The correlation between water-carbon and urban spatial form in built-up areas: Evidence from Shenzhen City, China. Urban Climate 59, 102292.

Wang, S., Li, G., Fang, C., 2018. Urbanization, economic growth, energy consumption, and CO2 emissions: Empirical evidence from countries with different income levels. Renewable and Sustainable Energy Reviews 81, 2144–2159.
Wang, Y., Lv, W., Wang, M., Chen, X., Li, Y., 2023. Application of improved Moran's I in the evaluation of urban spatial development. Spatial Statistics 54, 100736.

Wu, Y., Li, C., Shi, K., Liu, S., Chang, Z., 2022. Exploring the effect of urban sprawl on carbon dioxide emissions: An urban sprawl model analysis from remotely sensed nighttime light data. Environmental Impact Assessment Review 93, 106731.

Xia, C., Xiang, M., Fang, K., Li, Y., Ye, Y., Shi, Z., Liu, J., 2020. Spatial-temporal distribution of carbon emissions by daily travel and its response to urban form: A case study of Hangzhou, China. Journal of Cleaner Production 257, 120797.

Zuo, S., Dai, S., Ren, Y., 2020. More fragmentized urban form more CO2 emissions? A comprehensive relationship from the combination analysis across different scales. Journal of Cleaner Production 244, 118659.