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Research article

Exploring urban compactness impact on carbon emissions from energy consumption: A township-level case study of Hangzhou, China

Weiwu Wang [a,b,*,1], Yaozhi Luo [a], Jingyi Liang [a], Siwei Chen [c]

[a] College of Civil Engineering and Architecture, Zhejiang University, Hangzhou 310058, China
[b] Institute of Urban and Rural Planning Theory and Technology, Zhejiang University, Hangzhou 310058, China
[c] School of Urban Design, Wuhan University, Wuhan 430072, China

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ABSTRACT

Given that cities are the major contributors to carbon emissions, studying urban compactness (UC) and its impact on carbon emissions from energy consumption (CEECs) is crucial. This study calculated Hangzhou's township-level urban UC and CEECs using a hybrid subjective-objective weighted regression model on integrated panel datasets. By employing a geographically weighted regression (GWR) model, the spatio-temporal heterogeneity of the UC-CEEC relationship from 2006 to 2019 was uncovered. The results indicated an overall increase in UC, with significant variations across different counties. CEECs were higher in the central region, shifting eastward due to distinct urban development levels and policies. Moreover, the effects of various UC factors exhibited significant spatiotemporal inconsistency, with the impact intensity gradually diminishing. Additionally, the explanatory power of these factors declined and diversified over time. These findings emphasize the need for a comprehensive understanding of the relationship between UC and CEECs within the complex metropolitan environment and the importance of regulating their coordinated development. The research not only offers a more scientific approach to managing the growth of county-level cities and supporting balanced urbanization but also presents policy recommendations.

1. Introduction

Urban greenhouse gas emissions come mainly from urban energy consumption associated with production and land use [1]. Global carbon emissions reached a record high of 3.63 billion tons in 2021, of which China contributing 28 %, making it one of the world's largest emitters [2,3]. Large quantities of emissions are mainly concentrated in four major sectors: industry, construction, transportation and agriculture, which together account for 88.22 % of China's total carbon emissions [4,5]. With the booming economy and accelerated urbanization, the demand for energy by Chinese residents continues to grow [6]. Population, economic activity and industrial production are concentrated in urban areas, thus placing a huge environmental burden on cities. Metropolises with high energy demands are particularly prone to high levels of carbon emissions, which can lead to environmental issues and thus adversely

* Corresponding author. B610, Anzhong Building, Zijingang Campus, Zhejiang University, 866 Yuhangtang Road, Hangzhou 310058, China.
E-mail addresses: weiwuwang@zju.edu.cn (W. Wang), Luoyz@zju.edu.cn (Y. Luo), liangjingyi0721@zju.edu.cn (J. Liang), 20212820090044@whu.edu.cn (S. Chen).

[1] First Author.

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affect the quality of urban life. Urban centers have long been the focal of carbon emission control in China, accounting for 58 % of the total energy-related carbon emissions from Chinese residents [7]. Previous studies have shown a correlation between urban compactness (UC) and urban sprawl, which in turn affects carbon emissions resulting from transportation and energy consumption within cities [8,9].

Furthermore, UC has been found to exhibit strong connections with various urban challenges such as urban sprawl, inner-city poverty, long commuting distances, and social isolation [10–12]. A number of studies have highlighted that the combination of mixed land use, high urban density, and compact urban spatial forms can significantly reduce carbon emissions stemming from transportation [13–15]. Urban spatial patterns play a crucial role in the heat island effect and energy consumption of buildings, and also have a direct impact carbon emissions from energy consumption (CEECs) [11]. Suitable compact city development patterns can greatly contribute to the sustainable growth of China's metropolitan areas [16].

Some Chinese scholars' studies have explored the impact of UC on CEECs using empirical methods[17,18]. However, it is a challenge to fully understand the UC-CEEC relationship through quantitative analysis of spatial morphology alone. Studies on compactness measurements often use urban form as an initial consideration to explore the impact of indicators characterizing urban compactness on carbon emissions [19–23]. However, when analyzing township-level data, other factors that impact UC, such as population, economy, and morphology, must also be considered. In addition, most existing studies investigate the UC-CEEC relationship at a macro level, yet their findings exhibit inconsistency. Only a few researchers have examined this relationship at a micro level, focusing in particular on the interior spaces of metropolitan areas [18,24,25].

To address these research gaps, this study conducted a case study in Hangzhou to investigate the spatial heterogeneity of the relationship between urban compactness (UC), socioeconomic attributes, and carbon emissions from energy consumption (CEEC). Hangzhou provides unique advantages as a case study. As a relatively developed city, Hangzhou exhibits distinctive characteristics in urban planning and transportation systems, particularly in promoting sustainable development. This provides valuable insights for investigating the impact of UC on CEEC. Additionally, this study proposed a method to enhance the coordination between UC and CEEC at the township level. Compared to the city scale, the spatial granularity at the township level is finer, offering more detailed and specific geographic information. This is crucial for understanding the spatiotemporal trends of UC and CEEC and aids in formulating more targeted carbon reduction strategies.

The main contribution of this study lies in its comprehensive and innovative approach, specifically in the following aspects. First, this study developed a systematic framework and methodology from multiple perspectives, including social, economic, and spatial dimensions, to assess UC and CEEC. This framework encompasses a more comprehensive set of evaluation indicators, enabling a more accurate reflection of complex urban dynamics. Second, this study combines subjective and objective UC evaluation methods and employs a geographically weighted regression (GWR) model to categorize and analyze the relationships between social, economic, and spatial factors influencing UC and CEEC. Compared to previous studies, GWR model includes more variables, providing a more scientifically robust method for assessing the global and local impacts of UC. Furthermore, this study utilizes a comprehensive dataset

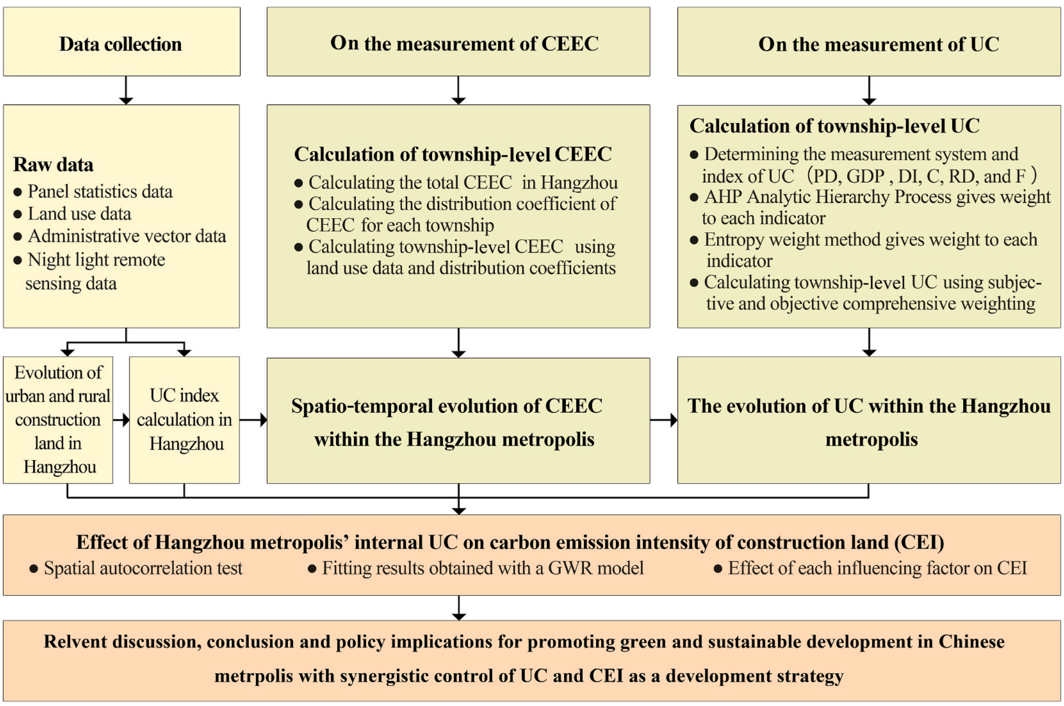


Fig. 1. The flowchart of the study.

at the township level to deeply analyze the spatiotemporal heterogeneity of UC's impact on CEEC. The innovation of this study lies in its micro-level revelation of finer spatial variations, offering a deeper understanding of intra-city heterogeneity, thus addressing the shortcomings of past research. Through this innovative approach, this study not only enriches the theoretical understanding of the UC-CEEC relationship but also provides more targeted insights for future urban planning and environmental policymaking. Fig. 1 visualizes the entire technical flow of this study.

2. Literature review

2.1. Research on the measurement of UC

Currently, a considerable amount of research is based on various dimensions and key indicators to measure urban compactness, yet a unified understanding is still lacking. The mainstream measurement methods of Urban Compactness (UC) can be broadly categorized into single-index measurement and multi-index measurement, with the latter being more widely used by scholars. The single-index measurement employs statistical or remote sensing data to calculate a comprehensive index characterizing UC. For instance, Wei et al. [26] measured UC by calculating the ratio of the area occupied by the largest urban block to the total urban area, known as the Largest Patch Index (LPI). The multi-index measurement method involves establishing a comprehensive evaluation index system using data from multiple dimensions, followed by a comprehensive assessment to determine UC. For example, Yu et al. [27] combined physical space, social space, urban function, and social activity into a four-dimensional framework, selecting eight indicators, including population, GDP, road density, building density, and land-use information, to construct the UC index system. UC was then measured using entropy weighting and expert scoring. However, this study only used data from a single year, providing insights into static measurements of UC. In another study by Fan et al. [28], UC was measured using density, land-use composition, street connectivity, centrality, and transit stops, with the assessment also based on data from a single year, making it difficult to measure changes in UC over time and space. In summary, single-index measurement methods are relatively simple and intuitive, making them suitable for inter-city comparisons but have limitations in comprehensively understanding UC, as they struggle to capture the complexity and diversity of cities. On the other hand, multi-index measurement methods consider various features of cities more comprehensively but involve more complex calculation and interpretation processes, and the determination of weights may be influenced by subjective judgments.

While significant progress has been made in measuring UC in existing studies, there are still some limitations. For example, some studies overlook temporal and spatial dynamic factors, focusing solely on static urban features without delving into their developmental changes. Secondly, the assessment framework in existing research is relatively incomplete, lacking comprehensive multidimensional considerations. Additionally, some studies rely on subjective judgments or simplified models, thus affecting the accuracy and reliability of analytical conclusions. To address these limitations, this study utilizes dynamic panel data from 2006 to 2019 and conducts analysis at a finer township level. Furthermore, this study establishes a comprehensive evaluation system comprising GDP, population density, development intensity, road density, shape index, and fragmentation index. Moreover, this study employs a combined weighting method, integrating subjective and objective factors, to measure UC more accurately. Compared to previous methods, this approach is more scientific and practical, providing a finer evaluation tool for future urban planning and policymaking.

2.2. Research on the measurement of urban CEECs

In recent years, technological innovation and the development of the digital economy have played an increasingly important role in carbon emissions management. For example, the findings of Zhang et al. [29] indicate that digital infrastructure reduces urban carbon emissions intensity by promoting industrial upgrading, reducing resource dependency, and fostering green innovation. Zhao et al. [30] revealed significant spatial spillover effects of digital inclusive finance on urban carbon emissions intensity, with more pronounced effects in cities with similar economic characteristics. Zhang and Zeng [31] found that artificial intelligence effectively reduces enterprise energy consumption by facilitating technological innovation and digital transformation. These studies underscore the crucial role of technological innovation and the digital economy in mitigating carbon emissions.

Concurrently, various methods have been employed to quantify carbon emissions, including the carbon footprint method, sample measurement method, remote sensing estimation, and building energy consumption simulations [32,33] The commonly employed method currently involves calculating carbon emissions using the CO_2 conversion factors defined in the Intergovernmental Panel on Climate Change (IPCC) Greenhouse Gas Inventory Guidelines. Subsequently, the calculated CO_2 conversion coefficients are utilized to determine the total carbon emissions for each type of energy source [34]. Hutyra et al. [35] employed the sample plot inventory method and carbon density data for different land use types, along with land use and land cover distribution in Seattle, Washington, to calculate carbon emissions for the city and track emissions changes with land use alterations. In the research conducted by Zhang and Luo [36], a calculation framework for CEECs targeting public buildings in China was proposed, employing the Building Energy Consumption Simulation method in conjunction with the Long-range Energy Alternative Planning system (LEAP) model.

However, there is a current issue in the research, namely the lack of comprehensive investigation into CEECs at the township level, primarily due to limitations in statistical data. To address this shortfall, we conducted targeted surveys specifically at the township level in major urban areas. Utilizing remote sensing nighttime light data, we estimated CEECs to circumvent data limitations and potential biases from variable data quality at the township level. The application of this method will help reveal the spatiotemporal dynamics of CEECs at the township level.

2.3. Research on the relationship between UC and CEECs

In recent research, despite the endeavors of a limited number of researchers to explore the correlation between urban compactness (UC) and carbon emissions from energy consumption (CEECs), the overall body of relevant research remains relatively constrained. Most of these studies employ Ordinary Least Squares (OLS) regression models, Geographically Weighted Regression (GWR) models, Multi-scale Geographically Weighted Regression (MGWR) models, and Geographically and Temporally Weighted Regression (GTWR) models to reveal the association and interactions between UC and CEECs at the metropolitan scale. For instance, Shi et al. [37] empirically analyzed 256 cities in China, unveiling spatiotemporal heterogeneity in the impact of UC on CEECs and suggesting co-ordinated efforts across environmental, economic, and social dimensions to maximize urban benefits and minimize carbon emissions. Hong et al. [38] provided a comprehensive review of the relationship between UC and CEECs, emphasizing that higher urban compactness implies increased connectivity, thereby reducing carbon emissions by minimizing commuting distances and times.

To date, there has been insufficient understanding of the relationship between UC and CEECs. Existing studies have primarily focused on the urban scale, failing to delve into nuances, particularly at finer spatial scales. This study aims to fill this research gap by analyzing at the township level, revealing urban heterogeneity, and deepening the understanding of the relationship between UC and CEECs. It provides targeted insights for sustainable urban development and environmental policy formulation.

3. Study Area and Data Source.

2.4. Overview of study area

Hangzhou city (118°21′E–120°30′E, 29°11′N–30°33′N) is situated in eastern China, specifically in the southern part of the Yangtze River Delta urban agglomeration, the lower reaches of the Qiantang River, and the southern section of the Beijing-Hangzhou Grand Canal. As the capital of Zhejiang Province, Hangzhou holds great significance in the Yangtze River Delta region and the Greater Bay Area surrounding Hangzhou Bay. The industrialization level of Hangzhou is relatively high, with rapid economic development in recent years, and the industrial sector playing a crucial role. In the most recent administrative division of Hangzhou in 2021, the city consists of 10 districts, 2 counties, and 1 county-level city, covering a total area of approximately 16,850 km^2 (Fig. 2). Benefiting from its convenient geographical location and regional advantages, Hangzhou has attracted a substantial population migration from the central and western regions of China. Energy consumption in Hangzhou is highly concentrated, with the primary sectors of consumption being the construction industry, transportation, and industrial sectors[39,40]. The construction industry is a significant source of energy consumption and carbon emissions. The high demand for heating, air conditioning, and lighting systems has led to substantial carbon emission spillover effects in this sector. In response to these challenges, the Hangzhou government has actively implemented a series of policy measures aimed at addressing carbon emissions and promoting sustainable development. For instance,

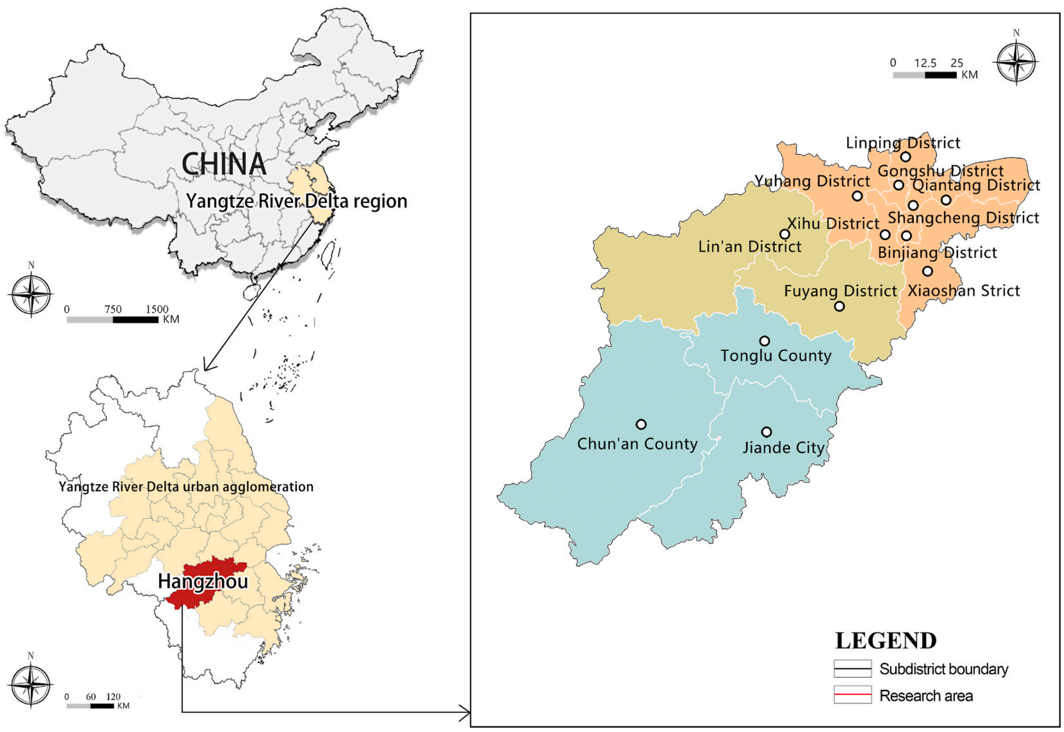


Fig. 2. Geographical location and administrative division of Hangzhou metropolis.

in 2016, Hangzhou launched a community energy-saving intervention program, which significantly enhanced residents' awareness and adoption of energy-saving technologies through the promotion of energy-efficient appliances[41], the implementation of building energy retrofits, and the conduct of energy-saving education campaigns. This provides an ideal research area to investigate and analyze the impact of UC on CEECs in Hangzhou. This study divides Hangzhou into three distinct regions based on economic disparities, urban planning dynamics and different developmental trajectories. The primary urban area is a thriving economic center with a concentration of commercial and service activities. Lin'an District and Fuyang District, on the other hand, are in a period of economic growth and industrial transformation. The three municipal counties, on the other hand, are areas of relative rural or secondary urban development. This division highlights the unique characteristics inherent in each area and is the basis for subsequent analysis.

2.5. Data sources

Data sources for this study include urban statistics, remote-sensing nighttime light data, and administrative district vector data. Urban statistics encompassed land use, population, and energy consumption. Population data were sourced from the Hangzhou Statistical Yearbook and the Township Demographic Data published by the Hangzhou Public Security Bureau, covering the period from 2006 to 2019. GDP kilometer grids were obtained from the Data Center for Resource and Environmental Sciences of the Chinese Academy of Sciences (http://www.resdc.cn). Remote-sensing nighttime light data were acquired from two datasets: DMSP_OLS V4 (1992–2013) and VIIRS_VNL V2 (2012–2020). After data correction, noise reduction, and dimensionality reduction fitting, these datasets were transformed into long time series images capturing stable lighting conditions at night. Administrative divisions and land use data encompassed China's national borders, provincial and municipal administrative division maps, as well as administrative division maps specific to Hangzhou, which were derived from the National Geographic Information Resource Catalog Service System (https://www.webmap.Cn/main.do?method = index). The road vector dataset includes Hangzhou highways, national highways, provincial highways and county highways, and the data are obtained from OpenStreetMap platform (https://master.apis.dev.openstreetmap.org) and Gaode Open Platform (https://lbs.amap. com/).

3. Research methods

3.1. Calculation of township-level CEECs

This study approached the calculation of township-level CEECs in three distinct steps.

Step 1. Determining the overall CEECs in Hangzhou's metropolitan areas

Based on the 2006 IPCC National Greenhouse Gas Emission Inventory Guidelines, the China Energy Statistical Yearbook, and detailed statistical data on Hangzhou's energy consumption from 2006 to 2019, the following methodology was employed to accurately estimate the carbon dioxide (CO_2) emissions generated from energy consumption in Hangzhou:

$$\mathrm{C} = \sum_{i=1}^{n} Ei \times fi \times Ki \tag{1}$$

where n is the total number of energy types, i is the type of energy, Ei is the actual consumption (10,000 tons), fi is the standard coal conversion factor of the ith energy type (tons of standard coal/ton of energy), and Ki is the carbon emission coefficient of the ith energy type (10,000 tons) carbon per 10,000 tons of standard coal. The standard coal conversion coefficient and carbon emission coefficient for each energy source are provided in Table 1.

Although the consumption of secondary energy sources (electricity and heat) does not directly generate carbon emissions, considering the overall carbon footprint of these energy sources, indirect carbon emissions, and the complexity of understanding the supply chain, and in order to contribute to a comprehensive analysis of the urban energy system from a more in-depth perspective, secondary energy sources, such as electricity and heat, are included in this study to provide a more comprehensive understanding of the urban carbon footprint.

Step 2. calculating the distribution coefficient of CEECs for each township.

In this study, the calculation of the distribution coefficient for the CEECs in each township was conducted as follows:

$$P_i = C' \times \Sigma_{n=1}^{m} \alpha_{in} \times \beta_i \tag{2}$$

where Pi is the CEECs of the ith township unit, C' is the CEECs in Hangzhou in a certain year, α_{in} is the carbon emissions coefficient of the nth type of land in the ith township unit. The carbon emissions coefficient for construction land in Hangzhou (t/hm^2) was

Table 1
Conversion coefficients and carbon emission coefficients of standard coal for each energy source.

Energy type	Raw coal	Coke	Crude	Gasoline	Kerosene	Diesel fuel	Fuel oil	Natural gas	Heat	Electricity
f_i	0.7143	0.9714	1.4286	1.4714	1.4714	1.4571	1.4286	1.33	0.03412[a]	0.345
K_i	0.7599	0.855	0.5857	0.5538	0.5714	0.5921	0.6185	0.4483	0.67	0.272[a]

[a] Note: The thermal conversion factor is kg standard coal/MJ, and the electricity conversion factor is kg/kWh.

determined by dividing the total carbon emissions of Hangzhou in a specific year by the total area of construction land. The carbon emissions coefficients for forests, grassland, and cultivated land were computed as −0.581, −0.0210 [42], and 0.4970 [43] t/hm^2, respectively. Parameter β_i represents the population coefficient of the township unit, which signifies the ratio of the population density in the ith township unit to that of Hangzhou city. The variable m denotes the number of land types within the township unit.

Previous studies have shown that nighttime light images have the potential to provide accurate population density data [44]. Additionally, research suggests a strong correlation ($R^2 > 0.96$) between DMSP nighttime brightness values and population sizes in major Chinese cities such as Beijing, Guangdong, and Tianjin [45]. In this study, nighttime light images of Hangzhou were utilized to obtain the annual population density coefficients for each town.

$$\beta_i = DN_i / DN_i' \tag{3}$$

DNi represents the total pixel brightness value of *DN* for nighttime lighting in the ith township unit, while *DN'* represents the total value of *DN* for nighttime lighting in Hangzhou.

Step 3. visualizing township-scale CEECs in ArcGIS9.3 software of ESRI

Using the graduated color tool and the geometric interval method in ArcGIS9.3 software of ESRI, the distribution coefficients of CEECs for each township obtained in the step 2 were classified into five levels and then visualized.

3.2. Calculation of UC based on subjective and objective comprehensive weighting

In order to assess the potential impacts of UC on CEEC, various indices ranging from social, economic and spatial aspects of GDP per square kilometer, population density, development intensity, road density, shape index and fragmentation index were used (See Table 2). The main purpose is to measure the extent of UC in Hangzhou and its potential impact on carbon emissions.

Due to the limitations associated with a single subjective or objective weighting method, this study employed a combination of subjective and objective weighting approach for weight calculation. This method effectively mitigated the adverse effects of outlier indicator weights, resulting in the computation of urban compactness values. The subjective approach utilized the Analytic Hierarchic Process (AHP), while the objective approach employed the Entropy weight method. During AHP analysis, the 1–9 scaling method was employed, relying on the expert opinions of eight specialists to systematically assess the relative importance of each indicator. A judgment matrix was constructed to facilitate weight calculations [52]. The obtained factor weights underwent normalization processing and consistency testing. The entropy weight method determined the weights of each indicator based on the relative information content provided by the observed values of each indicator. It reflected the utility value of the entropy of indicator information, effectively mitigating subjective influences [53]. The process involved constructing the original index data matrix (assuming m evaluation objects and n evaluation indicators) and standardizing the data for each indicator to eliminate the impact of varying dimensions and magnitudes. Under the *j*th index, the index proportion and information entropy of the *i*th evaluation object were calculated.

At last, the weight for each evaluation index was determined using the following equation:

$$W_j = k_1 W_1 + k_2 W_2 \tag{4}$$

where W_1 is the index weight obtained using the subjective method; W_2 is the index weight obtained using the objective method; and k_1 and k_2 represent the contributions of the subjective and objective methods, respectively. In this study, k_1 and k_2 were 0.5.

Based on the weights assigned to each indicator obtained through this method, along with the product of the standardized values, the final comprehensive score for urban compactness is calculated using the following equation:

Table 2
Hangzhou's internal compactness measurement system and index weights.

Index	Calculation formula	Index meaning	Reference
GDP per square kilometer *GDP*	$GDP_i = \sum_{i=n} GDP_j / n$	GDP_i is *i* study unit GDP per square kilometer; GDP_j is the raster cell value after spatialization; *n* is the total number of grids in the *i* th study unit	[46]
Population density *PD*	$PD_i = P_i / D_i$	PD_i is *i* study unit population density, P_i is *i* study unit total population, D_i is *i* study unit total area	[47]
Development intensity DI	$DI_i = A_i / D_i$	DI_i is *i* study unit development intensity, A_i is *i* study unit developed land area, D_i is *i* study unit total area	[48]
Road density *RD*	$RD_i = L_i / D_i$	RD_i is the road density of *i* study unit, L_i is the road length of *i* study unit, D_i is the total area of *i* study unit	[49]
Shape index *C*	$C_i = 2\sqrt{\pi A_i} / D_i$	C_i is the shape index of *i* study unit construction land, A_i is *i* study unit developed land area, and D_i is *i* study unit construction land perimeter. The value of C_i is between 0 and 1. The larger the value, the closer to 1, the closer the shape is to a circle, the higher the shape compactness; otherwise, the lower the shape compactness. This index provides a quantitative measure of the shape of an area and the degree of density or compactness within that region.	[50]
Fragmentation index *F*	$F_i = N_i / A_i$	F_i is the fragmentation index of the *i* study unit construction land, N_i is the total number of *i* study unit construction land patches, and A_i is the *i* study unit developed land area. The larger the value of F_i, the greater the fragmentation of the construction land.	[51]

$$S_i = \sum_{j=1}^{n} W_j \cdot X_{ij} \tag{5}$$

where W_j is the index weight obtained through the combination of the subjective and objective methods ($i = 1, 2, 3, \ldots, m$; $j = 1, 2, 3, \ldots, n$), and X_{ij} is the jth evaluation index of the ith evaluation object.

3.3. Construction of a geographically weighted regression model

In order to objectively reflect the impact of various factors on the carbon emission intensity in Hangzhou, this study utilized the Geographically Weighted Regression (GWR) model for analysis. The GWR model allows for the application of different regression coefficients at various geographical locations, providing a more accurate capture of spatial heterogeneity [54]. By comprehensively considering spatial variations, this study can gain a deeper understanding of the relationship between CEI and its influencing factors. Using the Geographically Weighted Regression (GWR) tool in ArcGIS software, this study constructed a GWR model for the CEI of construction land and its influencing factors in Hangzhou. The model bandwidth was determined based on the Akaike Information Criterion corrected (*AICc*), and fitted models were established for the years 2006, 2010, 2015, and 2019. The GWR model can be expressed as follows:

$$y_i = \beta_0(u_i, v_i) + \sum_{k=1}^{n} \beta_k(u_i, v_i)x_{ik} + \varepsilon_i \tag{6}$$

where y_i and x_{ik} are the dependent variable and independent variable of the local regression equation of the ith observation point, respectively; (u_i, v_i) are the geographic coordinates of the ith observation point; β_k (u_i, v_i) is the regression coefficient of the kth explanatory variable of the ith observation point; n is the number of explanatory variables; β_0 (u_i, v_i) is the intercept term of the regression model for the ith observation point; and ε_i is the independent and identically distributed random error term.

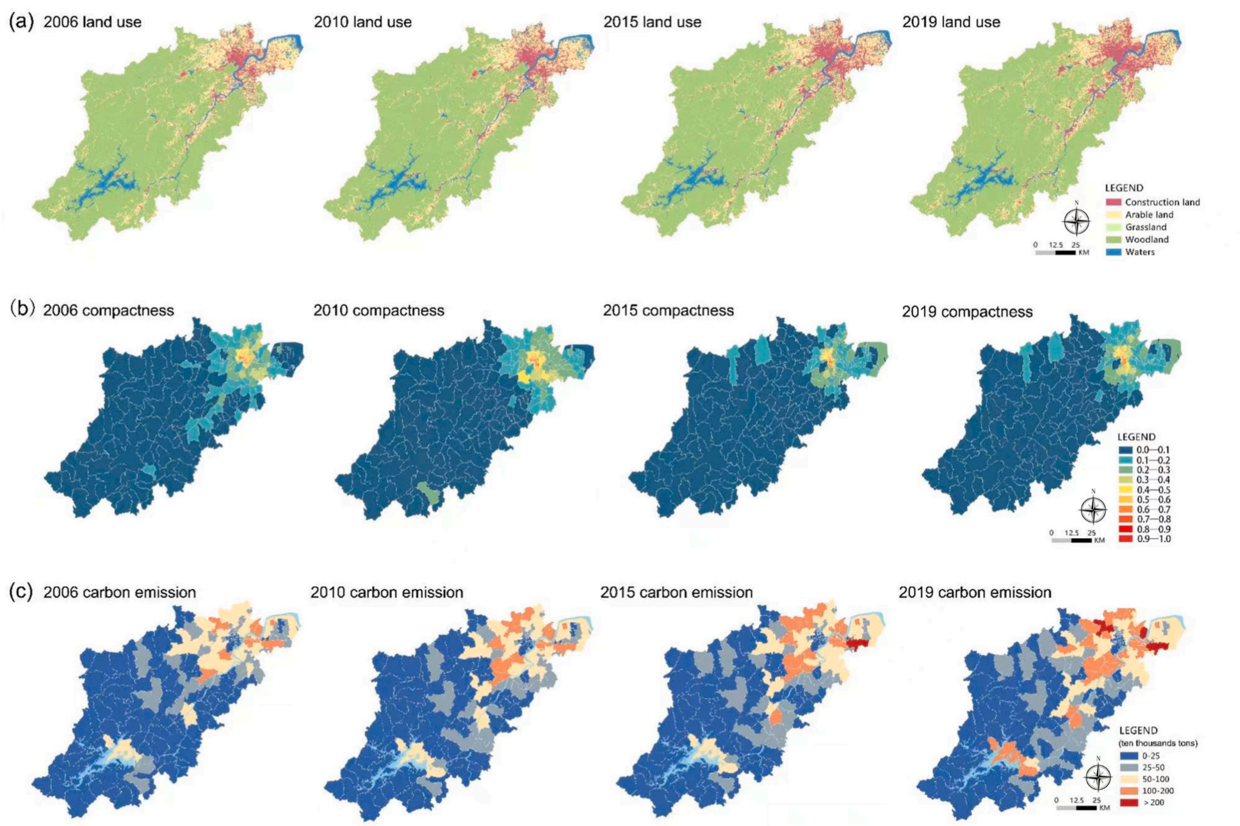


Fig. 3. The evolution of land use, internal township-level compactness and carbon emission density levels in Hangzhou from 2006 to 2019. (a) Land use; (b) internal township-level compactness; (c) carbon emission density levels.

4. Results and discussion

4.1. Evolution of urban and rural construction land in Hangzhou

Spatial variations in the distribution of construction land in Hangzhou were observed, as shown in Fig. 3a. In previous years, the majority of construction land was concentrated in the main urban area towards the northeast, with smaller scattered clusters found in the western and southern regions near the water system. This distribution pattern can be attributed to the physical and geographical characteristics of Hangzhou. Situated in the Qiantang River Basin, Hangzhou boasts rivers, lakes, and mountains. The northeastern portion of the city falls within the North Zhejiang Plain, characterized by low-lying and flat terrain. Meanwhile, the mountainous areas impose significant limitations on the expansion of urban and rural construction land. Over time, the size of the construction land in the main urban area substantially increased, and the density of construction land also grew along both sides of the Qiantang River. By converting portions of cultivated land into construction land, the peripheral areas of the urban region gradually expanded into the river valleys in the west and southwest, ultimately connecting with the main city. From 2006 to 2019, there was a consistent expansion in the area occupied by construction land.

The expansion of construction land in Hangzhou was assessed and evaluated by analyzing and comparing the average annual growth and growth rate of construction land in different periods (Table 3). Generally, construction land in Hangzhou consistently increased over the study period. In 2006, the total area of construction land was 907.83 km^2, which grew to 1109.18 km^2 in 2010 and further to 1352.71 km^2 in 2015. By 2019, the area had reached 1454.92 km^2. The average annual growth rate of construction land was highest during the period from 2006 to 2010. The growth rate slightly decreased during the period from 2010 to 2015, but remained significant. Notably, from 2015 to 2019, the growth rate of construction land decreased considerably, with the average annual growth during this period being half that of the 2006–2010 period. This shift indicates a transition in the expansion of construction land in Hangzhou, moving from a phase of large-scale expansion to a period of more refined growth between 2006 and 2019.

4.2. The evolution of UC within the Hangzhou metropolis

The weights assigned to the GDP per square kilometer, population density, development intensity, road density, shape index, and fragmentation index, as proposed in Section 4.2 to calculate UC, were 0.220, 0.231, 0.164, 0.229, 0.130, and 0.025, respectively. These indicators were utilized to compute the UC for each township (street) in Hangzhou in 2006, 2010, 2015, and 2019, and the average UC was derived for the city and county levels (Table 4). The internal UC of Hangzhou exhibited a pattern of initial increase, subsequent decrease, and subsequent increase from 2006 to 2019. The UC reached its lowest point in 2015, and significant variations in UC were observed across the different counties and districts.

Gongshu and Shangcheng had the highest levels of UC in Hangzhou, followed by Binjiang in third place, and then Xihu, Linping, Xiaoshan, Qiantang, Yuhang, and Fuyang. On the contrary, the areas with the lowest UC values were Tonglu County, Lin'an, Jiande County, and Chun'an County. The differences in UC were mainly attributed to differences in urban development. Gongshu and Shangcheng, as the most developed urban areas, were smaller in size, had high population density, and intense development. In contrast, neighboring counties like Jiande County and Chun'an County were larger in size and had hilly terrain. These areas were relatively underdeveloped economically, with insufficient infrastructure and spatial connectivity of construction land, and uneven distribution of river valleys and water systems. As a result, the UC in these areas remained relatively low.

Fig. 3b illustrates the temporal evolution of the urban compactness index (UC) within Hangzhou. In 2006, areas with high UC were relatively small and primarily concentrated in the western parts of Shangcheng District and Gongshu District, situated on the northern bank of the Qiantang River. Additionally, high UC was also observed in the southern and northeastern regions of Xihu District, specific parts of Binjiang District, the southern region of Linping District, and the northern region of Xiaoshan District. By 2010, the areas exhibiting high UC had expanded, with notable increases in compactness observed in several plots on the southern bank of the Qiantang River. This period witnessed rapid urban development and cross-river expansion in Hangzhou. The construction land on both banks of the Qiantang River experienced significant expansion, particularly in the southern bank area. The flat topography facilitated the continuous improvements of the infrastructure network and the gradual transformation of large areas of arable land into a variety of land use types. The convergence of residential, productive and public service land uses had attracted a large population, leading to the increased UC of the southern bank area.

The most notable change observed in 2015, was the increase in UC in the western and southern sections of Hangzhou's main city. This shift can be attributed to the improved transportation network, which strengthens the connectivity of cities in peripheral regions such as Yuhang and Fuyang, thus affecting the UC of these cities. In 2019, the size of high-population-density regions expanded significantly, with areas including Uptown, Gongshu, Xihu, Binjiang, Linping, and Xiaoshan exhibiting medium-to-high densities. From 2015 to 2019, the expansion of construction land size in regions such as Xiaoshan, In the central area of the main city, infill

Table 3
Changes in Hangzhou construction land area from 2006 to 2019.

	2006	2010	2015	2019
Construction land area (km^2)	907.83	1109.18	1352.71	1454.92
Average annual growth area (km^2)	–	50.34	48.71	25.55
Average annual growth rate (%)	–	5.54	4.39	1.89

Table 4
Variation trend of Hangzhou's internal UC from 2006 to 2019.

District (County)	2006	2010	2015	2019
Hangzhou (Average)	0.190	0.201	0.160	0.173
Shangcheng	0.449	0.477	0.423	0.445
Gongshu	0.518	0.545	0.430	0.445
West Lake	0.294	0.315	0.233	0.254
Binjiang	0.292	0.347	0.292	0.320
Xiaoshan	0.195	0.230	0.148	0.162
Yuhang	0.124	0.126	0.072	0.087
Linping	0.249	0.239	0.177	0.205
Qiantang	0.116	0.163	0.155	0.166
Fuyang	0.080	0.067	0.048	0.052
Lin'an	0.041	0.031	0.035	0.037
Jiande (County)	0.036	0.027	0.020	0.021
Tonglu (County)	0.047	0.029	0.022	0.024
Chun'an (County)	0.029	0.021	0.023	0.023

development was predominantly undertaken, leading to an expansion of its unified planning area.

4.3. Spatio-temporal evolution of CEECs within the Hangzhou metropolis

The distribution patterns of CEECs in Hangzhou for the years 2006, 2010, 2015, and 2019 were determined using the calculation method outlined in Section 4 (Fig. 3c). In Hangzhou, the CEECs were higher in the main urban area compared to the periphery, with areas displaying high CEECs located north of the Qiantang River. Some plots of land in the southern part of Hangzhou, particularly the central towns of peripheral counties and districts, exhibited high CEECs. The overall CEECs in the old urban area were lower in comparison to the surrounding regions. Between 2006 and 2019, there was an expansion of areas with high and medium-high CEECs, accompanied by a shift in the center of CEECs towards the east. Three factors help explain this change. Firstly, the expansion of Hangzhou resulted in improved public transportation networks, led by the Hangzhou Metro. This facilitated increased construction activity and population influx from various regions, thereby considerably raising carbon emissions associated with transportation. Secondly, Hangzhou's river development strategy led to a substantial increase in development intensity on both sides of the Qiantang River. Areas such as Qianjiang New City and Qianjiang Century City became crucial business centers with large populations and high living standards. Lastly, the rapid development of the Dajiangdong industrial cluster on the south bank of the Qiantang River attracted numerous secondary and tertiary enterprises, creating employment opportunities. This area, driven by high-tech industries, continually improved its living facilities, leading to the development of residential, commercial, and transportation infrastructure. Consequently, the CEECs of this region experienced significant increases over time.

4.4. Effect of Hangzhou metropolis' internal UC on carbon emission intensity of construction land

In order to investigate the relationship between internal compactness and carbon emissions within Hangzhou, the study utilized carbon emissions per unit area (km^2) of construction land (referred to as CEI) as the dependent variable. This approach facilitated the consideration of the significant variations in construction land area across each township (street). The study selected a series of compactness indicators as independent variables, including population density (PD), development intensity (DI), shape index (C), GDP per square kilometer (GDP), and fragmentation index (F), to examine the impact of various factors on carbon emissions. These measures aimed to capture the levels of compactness and development within each area. Given the evident spatial differences in construction intensity and carbon emissions among townships (streets), a GWR model was employed. This approach enabled the objective assessment of the localized effects of various factors on carbon emissions.

4.4.1. Spatial autocorrelation test

Spatial autocorrelation is the statistical relationship between the value of a specific attribute and its spatial location. This measure is

Table 5
Moran's I index analysis results of carbon emission intensity and influencing factors of construction land in Hangzhou.

variable	2006			2010			2015			2019		
	Moran's I	Z	P	Moran's I	Z	P	Moran's I	Z	P	Moran's I	Z	P
CEI	0.12	5.72	0.00	0.10	4.84	0.00	0.08	3.64	0.00	0.04	2.01	0.04
PD	0.64	86.28	0.00	0.68	86.26	0.00	0.72	87.94	0.00	0.75	86.97	0.00
DI	0.84	82.01	0.00	0.86	77.97	0.00	0.88	73.96	0.00	0.89	71.87	0.00
C	0.78	77.82	0.00	0.80	74.22	0.00	0.80	70.23	0.00	0.81	68.21	0.00
F	0.52	20.95	0.00	0.47	18.97	0.00	0.51	20.38	0.00	0.51	20.15	0.00
GDP	0.23	87.80	0.00	0.18	68.32	0.00	0.17	69.10	0.00	0.18	71.97	0.00
RD	0.29	11.56	0.00	0.01	0.64	0.52	0.03	1.43	0.15	0.03	1.43	0.15

typically assessed using the Moran's I index. ArcGIS was utilized in the study to calculate Moran's I index for the carbon emission intensity of construction land in Hangzhou, as well as the factors influencing this intensity. The Moran's I index assesses spatial autocorrelation in a dataset (range from −1 to 1). A value near 1 signifies positive spatial autocorrelation, forming clusters; near −1 indicates negative spatial autocorrelation, forming outliers. Close to 0 suggests randomness [55]. Z-score measures its significance (>|1.96| for 95 % confidence). A significant P-value (<0.05) rejects randomness [56]. The results showed that CEI, PD, DI, C, F and GDP exhibited significant positive spatial autocorrelation. However, the Road Density (RD) variable only displayed significant positive spatial autocorrelation in 2006, while no clear spatial autocorrelation was observed between 2010 and 2019 (Table 5).

4.4.2. Fitting results obtained with a GWR model

ArcGIS 10.2 software was used to establish a GWR model for analyzing Hangzhou's CEI and the influencing factors. The model's bandwidth was determined based on the Akaike Information Criterion corrected (AICc) for small sample sizes. The AICc is employed to balance the goodness of fit and the complexity of a model during the fitting process. Smaller AICc values indicate a better fit. The model that fits the data optimally without being overly complex can be chosen by comparing the AICc values of different models [57]. Four time points were considered: 2006, 2010, 2015, and 2019 within the model. The model fitting results are presented in Table 6. It is noteworthy that the goodness of fit (R^2) of the GWR model gradually decreased over time, suggesting that the explanatory power of the factors influencing CEI diminished over time, indicating an increased complexity in the relationships.

4.4.3. Effect of each influencing factor on CEI

The natural breakpoints method was employed to classify the regression coefficients obtained from the GWR model into five levels, allowing for the visual representation of the spatial distribution of regression coefficients for each influencing factor during different time periods. This enabled the analysis of the impact of compactness indicators on CEI within various regions of Hangzhou (Fig. 4).

Regarding the regression coefficients of GDP on CEI, except for individual areas such as Chun'an County, Jiande City, Tonglu County, and Lin'an District, positive regression coefficients were observed in all other areas. This suggests a generally positive impact of GDP on CEI (Fig. 4). It is worth noting that the average absolute values of these coefficients show a decreasing trend from 2006 to 2010, transitioning from a sharp increase to a steady increase from 2010 to 2019. These results suggest that the impact of GDP on the CEI initially diminishes, then increases significantly, and eventually stabilizes over the 2006 to 2019 period.

In most areas of Hangzhou, PD had a positive effect on CEI (positive regression coefficient). However, this effect was relatively weak in areas close to the main urban areas (Fig. 4). Interestingly, in some areas, such as Chun'an County, Lin'an City, Jiande City, and parts of the main urban area, PD had a negative impact on CEI, meaning that an increase in PD leads to a decrease in CEI. In the areas where population density (PD) had a positive impact, a fluctuating and weakening trend in the impact of PD on CEI from 2006 to 2019 is noted, with a significant peak from 2010 to 2015. Conversely, regions with negative impacts showed an upward fluctuating trend. In the more developed urban areas, complex building layouts dominated by high-rise buildings were created. Increased immigration had led to a surge in population density in various areas of Hangzhou, and newer construction methods had allowed the previously dispersed population to be concentrated in high-rise buildings. The centralized power and heating systems in these high-rise buildings helped to reduce energy consumption per unit area. Thus, the construction of high-rise buildings had mitigated to some extent the rise in CEI caused by urban development.

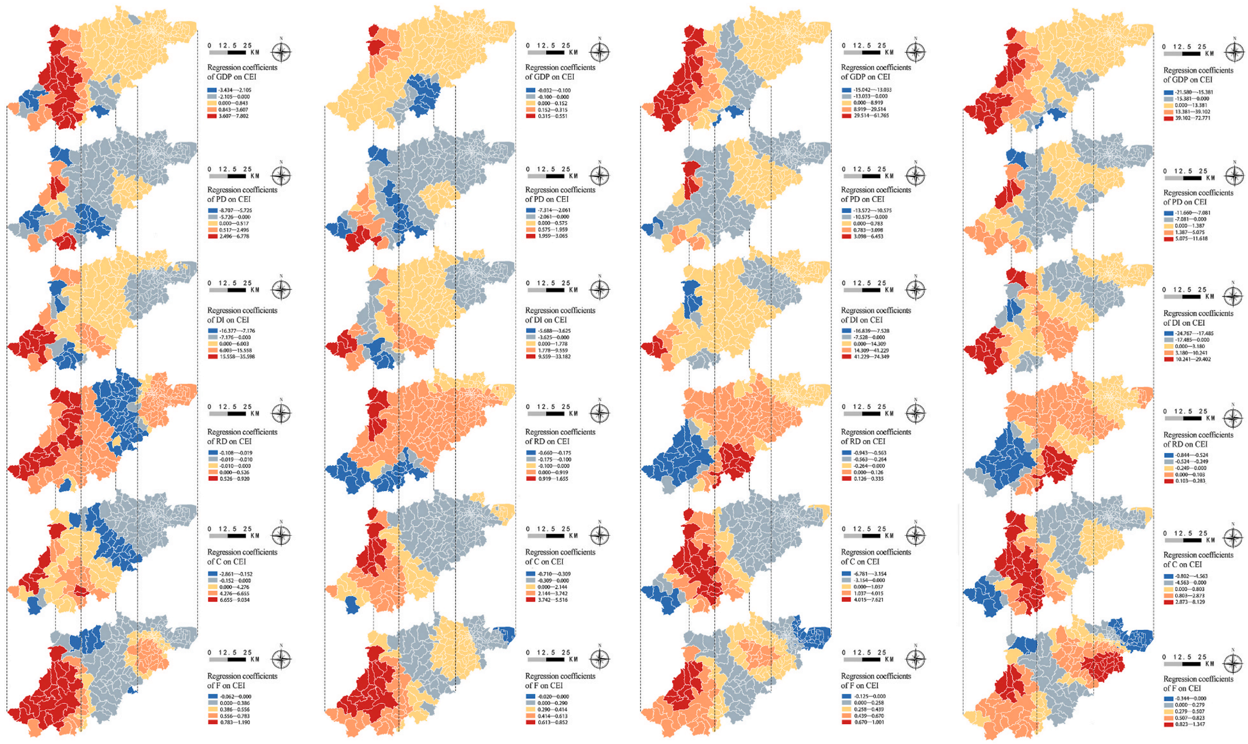
Fig. 4 illustrates the expanding positive impact of DI on Hangzhou's CEI. Examining the change in the absolute values of the positive regression coefficients, this study observes a gradual weakening and subsequent strengthening of DI's positive effect on CEI from 2006 to 2019. On the contrary, the absolute values of the negative regression coefficients demonstrated a fluctuating upward trend over the period 2006–2019, with a larger increase over the period 2010–2015.

Through analysis of specific time periods, it was found that from 2006 to 2010, the areas where DI significantly contributed to CEI were Jiande City and Chun'an County. However, from 2010 to 2019, these areas shifted to Chun'an County and Lin'an District, indicating a gradual decrease in the areas showing significant inhibitory effects. Therefore, it was concluded that Jiande City and Chun'an County were the districts where DI significantly impacted CEI from 2006 to 2010, whereas Chun'an County and Lin'an District exhibited this influence from 2010 to 2019.

As shown in Fig. 4, in Hangzhou, the degree of positive and negative effects of RD on CEI was similar. The absolute value of the positive regression coefficient showed an increasing trend from 2006 to 2010, then decreased sharply and weakens from 2010 to 2019. On the contrary, the absolute value of the negative regression coefficient increased sharply from 2006 to 2015 and stabilized from 2015 to 2019. Analyzing the time dynamics, it was found that the positive impact of RD on CEI initially rose from 2006 to 2019, then declined sharply and gradually weakened. Meanwhile, the negative impact exhibited an upward trend and eventually stabilized. When examining the spatial distribution of the regression coefficients, it was found that the areas significantly affected by RD on CEI

Table 6
GWR model fitting results.

Residual Squares	2006	2010	2015	2019
	0.403	0.579	0.761	1.201
Sigma	0.052	0.059	0.071	0.090
AICc	−565.716	−527.236	−447.474	−349.000
R^2	0.714	0.563	0.541	0.498
Adjusted R^2	0.631	0.487	0.418	0.346



(a) 2006 (b) 2010 (c) 2015 (d) 2019

Fig. 4. Regression coefficients of gross domestic product (*GDP*), population density (*PD*), development intensity (*DI*), Road density *(RD)*, shape index (*C*), fragmentation index (*F*) on *CEI* in 2006, 2010, 2015, 2019.

gradually decreased over time.

Fig. 4 depicts the spatial variation of the influence of the internal shape index C on CEI in Hangzhou. The northeastern part of Hangzhou mainly showed a negative influence, while the southwestern part showed a positive influence. From 2006 to 2019, the absolute value of the positive regression coefficient showed a trend of decreasing and then gradually increasing, which indicated that the effect of C on CEI showed a corresponding trend. On the contrary, the absolute value of the negative regression coefficient showed a decreasing and then increasing trend from 2006 to 2019. By analyzing the spatial distribution of the regression coefficients, it was found that the contribution of the shape index to the carbon emissions intensity (CEI) of construction land gradually expanded from a small part of Lin'an District, Chun'an County, and Jiande City to a large part of the region from 2006 to 2019. Meanwhile, the area with inhibitory effect shrank. Therefore, for the main urban areas with flat topography and limited development boundaries, the higher the spatial compactness of construction land, the larger the C value. However, over time, the area of building land increased to some extent, and the CEI also changed with the changes in building volume and function. Consequently, the influence of the shape index on CEI diminished progressively over time.

The regression coefficients of the impact of the construction land fragmentation index (F) on the CEI were predominantly positive, except for parts of the northeastern Quntang district and western Lin'an (Fig. 4). From 2006 to 2019, the region with the greatest impact of F on CEI gradually shifted from southwestern Quntang to eastern Fuyang, and the impacts of southwestern main city and eastern Lin'an gradually increased over time. In addition, the average of the 4-year regression coefficients increased over time, indicating that the impact of F on CEI wss gradually amplified. In the southwest of Hangzhou, due to the influence of natural geographic factors such as hills and rivers, the connectivity between patches of construction land was poor, resulting in a high degree of fragmentation of construction land. With the expansion of the city and transportation network, urban agglomerations in Fuyang, Lin'an and other surrounding areas continue to extend outward, leading to further fragmentation of construction land in Hangzhou. The fragmentation hindered the effective exchange of resources, resulting in a large amount of energy waste and ultimately leading to an overall increase in Hangzhou's CEI.

4.5. Discussion

The above analysis highlights the dual impact of China's urbanization and carbon neutrality efforts on economic development. At the same time, it is essential to emphasize the irreversible trend of rapid urbanization underway in China. With the acceleration of the urbanization process, the concentration of urban population and the growth of economic activities will continue to drive the vigorous development of urban economy[58]. However, this process also further underscores the interplay between socio-economic development and urban morphology in influencing carbon emissions [59]. The concentration of economic activities during urbanization leads to an increase in energy consumption and carbon emissions, while adjustments and changes in urban morphology also have significant implications for carbon emissions. Therefore, it is imperative to strengthen the management and control of carbon emissions while promoting economic development and urban planning to facilitate green and low-carbon economic development. To this end, the city has introduced a series of measures including the implementation of carbon neutrality, the establishment of a dual-carbon digital intelligence platform for energy, and the creation of a multi-level pilot system to promote zero-carbon and low-carbon initiatives [60,61].

In recent decades, while China's urbanization rate has experienced rapid growth, the spatial patterns of most cities have undergone transformations. The relationship between urban form and carbon emissions has been a topic of great interest among scholars for many years, leading to numerous studies [62–64]. However, the findings regarding the impact of different urban form characteristics on urban carbon emissions at the macro level, such as urban sprawl, compactness, monocentricity versus polycentricity, and morphological regularity, have been inconsistent. While many studies suggest that a compact urban form can help suppress carbon emissions and improve urban carbon performance [65–67], arguing that more compact cities have higher connectivity and are conducive to reducing carbon emissions [68], other studies have found that compact cities may actually hinder carbon performance [69,70]. Research examining the impact of compact or sprawling urban form on carbon emissions from specific sectors like transportation and buildings has primarily focused on the urban scale [71]. At smaller scales, studies have concentrated on the influence of urban form on carbon emissions resulting from work or lifestyle factors, such as residential mobility, household activities, and business operations [72,73]. Furthermore, it has been emphasized that carbon intensity level and utilization value are crucial in achieving the dual goals of sustainable socio-economic development and carbon emissions reduction in China [74].

This study represents a notable breakthrough in these domains:

(1) This study aims to present an innovative and efficient pathway towards achieving carbon neutrality goals in metropolitan areas, particularly in China, by exploring the intrinsic linkage mechanism between Hangzhou UCs and CEECs.
(2) This study aims to downscale the research scope from the city level to the township level, acknowledging the significance of understanding carbon emissions within metropolitan areas. Townships, as fundamental administrative units in Chinese cities, accommodate approximately 65 % of China's population, contribute to nearly 60 % of China's economic output [75], and account for approximately half of China's carbon emissions [76]). Furthermore, the establishment of healthcare and educational institutions, along with the development of road transportation systems and urban pipeline networks, significantly impact the overall carbon emissions across various sectors [77].
(3) When it comes to urban planning implementation, addressing the issue of urban compactness may appear more challenging than reducing carbon emissions. Therefore, achieving scientifically planned compact urban development does not solely involve reducing land resource demands; it also entails effectively controlling urban sprawl through efficient land and energy utilization.

5. Conclusions and policy implication

In this paper, the subjective-objective integrated weighting method and the CE model provided by IPCC are used to realize the measurement of UC and CEEC at the township level, and the influence of UC on CEEC is explored through the spatio-temporal analysis based on GIS and GWR, in order to hopefully contribute to the related research through the concept of urban development planning and spatial wholeness. The main conclusions of this study are as follows:

(1) The expansion of built-up areas in metropolitan regions is closely related to the degree of urban compactness (UC). The variations in UC are primarily attributed to disparities in urban construction levels, where higher UC is observed in densely populated and economically developed townships with well-established construction land infrastructure and spatial connectivity. In contrast, Hangzhou's suburbs face the challenge of poor spatial connectivity due to underdeveloped economies, inadequate facilities, and the presence of river valleys and waterways. Furthermore, urban development policies also play an important role in shaping these dynamics. The Hangzhou municipal government, for instance, introduced the "cross-river development" policy [78], leading to increased construction land development in areas around the main urban regions such as Xiaoshan, Yuhang, Fuyang, and Lin'an.
(2) UC and CEEC exhibit mutual influence and interdependence throughout the development process. From 2006 to 2019, UC, CEEC and their main influencing factors in Hangzhou metropolis show spatio-temporal heterogeneity. In general, there is a significant positive spatial autocorrelation among UC variables such as PD, DI, C, GDP, and F, with the exception of RI in the Hangzhou metropolitan area. However, the factors and degree of UC's impact on CEEC differ across different regions within the metropolitan area. The effects of GDP, DI, and F on CEI remain relatively stable and consistent in terms of spatial dimensions and temporal changes. Conversely, the impacts of RD and C exhibit greater dynamism. This indicates that the explanatory power of the UC factor for CEECs diminishes over time, and the relationship between them becomes more intricate.
(3) This investigation primarily centers around the connection between CEECs and CEIs with UC and its evolving social, economic, and spatial factors. Urbanization is a multifaceted socio-economic process that entails alterations in various dimensions. Existing research predominantly examines the influence of carbon emissions from the vantage points of urban social activities [79] and urbanization subsystems [80].

There are also some policy implications implicit in these findings:

(1) Considering the impacts from various factors, there is an urgent need to develop standardized guidelines for China's metropolises in order to keep urban compactness within reasonable limits. On the one hand, national or regional standards need to be developed to ensure consistency in assessing compactness in the urban planning process. On the other hand, urban compactness needs to be subject to a clear upper limit so that it is maintained at a reasonable level throughout the urban development process.
(2) The spatial relationship between UC and CEEC is analyzed to achieve effective and scientifically informed regulation of carbon emissions in urban areas. City governments should develop evidence-based policies that consider the impact of UCs on CEECs, aiming to promote low-carbon and efficient green urban planning and construction. In formulating these policies, it is crucial to consider strategies for promoting metropolitan control choices and establishing compact and low-carbon development patterns throughout China. The integrated regulation of UCs and CEECs should be seen as a strategic framework for metropolitan development. It is recommended to establish an integrated regulatory authority overseeing UCs and CEECs. Innovative policies should be considered to encourage cities to adopt cutting-edge technologies, incentivizing carbon emission and energy consumption reduction through rewards or subsidies. In addition, a performance assessment system should be established to evaluate cities on a regular basis so that policies can be adjusted in a timely manner.
(3) The formulation of rational and unified land use and its related control policies is the basis for promoting green development strategies within metropolitan areas. Since improving urban compactness in these areas is a gradual process, the implementation of well-designed urban compactness strategies can effectively optimize urban compactness and reduce CEECs. The formulation of appropriate control policies requires theoretical analyses of the impacts of urban compactness on CEECs, the identification of appropriate ranges of urban compactness, and the development of methods for adjusting the factors affecting urban compactness.
(4) To meet the challenges posed by urbanization, city planners are often faced with the dilemma of either directly reducing carbon emissions or addressing the underlying problem. However, the economic and social costs of direct carbon reduction measures can be significant for large metropolitan areas. Instead, the focus of promoting compact city development should be on policies that regulate urban sprawl and encourage the efficient use of land and energy resources, rather than aiming solely at reducing the demand for land resources. Such an approach provides a more effective and viable strategy for achieving sustainable urban development.

The findings and corresponding policy recommendations are applicable not only to Hangzhou and major urban areas of China but also to broader contexts of urban development and sustainability. The impact of UC on CEEC is a global issue encompassing vital topics such as worldwide urbanization and climate change. Countries worldwide face the challenge of maintaining environmental sustainability while experiencing rapid urbanization. Therefore, the findings of this study are anticipated to provide valuable experiences and insights for other international metropolises.

6. Study limitations

To enhance the precision of small-scale CEEC calculations, future studies should leverage multi-source open network data or employ methodologies such as carbon emission field collection and software numerical simulation to obtain more refined data. Moreover, the factors influencing social behavior, economy, environment, and culture are complex and diverse. While many indicators are challenging to quantify, some socio-economic variables such as energy structure and industrial technology were not included in this analysis. Further investigations are encouraged to address these limitations and advance the understanding in this field.

CRediT authorship contribution statement

Weiwu Wang: Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Project administration, Methodology, Investigation, Funding acquisition, Conceptualization. **Yaozhi Luo:** Writing – review & editing, Project administration, Conceptualization. **Jingyi Liang:** Writing – original draft, Visualization, Software, Investigation, Data curation, Conceptualization. **Siwei Chen:** Writing – review & editing, Visualization, Validation, Methodology.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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