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RESEARCH ARTICLE

Assessing the spatial spillover effects and influencing factors of carbon emission efficiency: a case of three provinces in the middle reaches of the Yangtze River, China

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Abstract
Studying urban carbon emission efficiency is vital for promoting city collaboration in combating climate change. Prior research relied on traditional econometric models, lacking spatial spillover effects understanding at the urban scale. To provide a more comprehensive and visually insightful representation of the evolving characteristics of carbon emission efficiency and its spatial clustering effects and to establish a comprehensive set of indicators to explore the spatial spillover pathways of urban carbon emission efficiency, we conducted an analysis focusing on 42 cities in the middle reaches of the Yangtze River. By employing the index decomposition method, the super-efficiency SBM model, spatial autocorrelation analysis, and the spatial Durbin model, the study calculates the urban carbon emission efficiency from 2011 to 2019 and analyzes the spatial spillover effects and influencing factors of urban carbon emission efficiency. The main conclusions are as follows: (1) Jiangxi Province displayed stable urban carbon emission efficiency evolution, while Hubei and Hunan showed significant internal disparities. (2) Positive spatial correlation exists in urban carbon emission efficiency, with an imbalanced distribution. (3) Various factors influence urban carbon emission efficiency. Technological innovation and economic development have positive direct and indirect impacts, whereas industrial structure, urbanization, population, and energy consumption have negative effects. Spatial spillover effects of vegetation coverage are insignificant. These methods and findings offer insights for future research and policy formulation to promote regional sustainable development and carbon emission reduction.

Keywords Carbon emission efficiency · Spatial spillover effects · Regional sustainable development · Spatial Durbin model

Introduction

The continuous growth of global carbon emissions poses a severe challenge to global socioeconomic development, and carbon emissions have become a critical factor influencing China's sustainable development. In 2021, China announced its carbon neutrality target, marking the first year of implementation and the beginning of the 14th Five-Year Plan. According to the "Global Energy Review: CO_2 Emissions in 2021" report released by the International Energy Agency, China was the only major economy that achieved economic growth in both 2020 and 2021. During these two years, China's carbon dioxide emissions increased by 750 million tons, surpassing the total emission reduction of 570 million tons in the rest of the world.[1] With the increasingly close collaboration among cities, China has continuously introduced relevant policies to promote the green and low-carbon transformation of key regions for economic development. For example, the "Implementation Plan for the Development of the Yangtze River Economic Belt in the 14th Five-Year Plan" emphasizes the promotion of green transformation in key industries and the transition from controlling the total energy consumption and intensity to controlling the total carbon emissions and intensity. In the face of the contradiction between economic development goals and emission reduction targets, improving carbon emission efficiency has

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[1] https://www.iea.org/reports/global-energy-review-co2-emissions-in-2021-2

become a crucial means to reduce carbon emissions and a key approach for China to promote socioeconomic sustainable development and fulfill its global environmental responsibilities (Tang et al. 2021).

Carbon emission efficiency (CEE) is a common indicator for measuring the effectiveness of regional energy conservation and emission reduction. It reflects the relationship between carbon emissions and the value created in a specific region (Zhang and Liu 2022). A higher CEE indicates that less carbon is emitted for the same level of output, indicating a relatively environmentally friendly performance. Data envelopment analysis (DEA) is widely used as an efficiency measurement method. However, it may introduce deviations in the measurement results due to the neglect of factors such as undesirable outputs and exogenous environment. To address this issue, some scholars have proposed improved methods, such as the slack-based model (SBM) (Choi et al. 2012), the super-efficiency SBM model (Meng et al. 2023), and the three-stage DEA model (Dong et al. 2017), which yield results that better align with the real-world conditions. To capture the spatiotemporal evolution of CEE, various methods such as the Theil index (Li et al. 2022), kernel density estimation (Xu et al. 2022), spatial autocorrelation (Yan et al. 2017), and spatial Markov chain (Qin et al. 2020) are widely used. These methods have demonstrated significant regional heterogeneity, clustering, and spatial correlation in CEE. Moreover, spatial driving factors for CEE, such as population, economic growth, technological progress, and urbanization level, have been considered in related studies (Zhou et al. 2019a, b; Sun and Dong 2022; Zhang et al. 2022a). This helps provide a more systematic and comprehensive understanding of spatial differences in CEE.

There has been significant progress in the calculation and discussion of CEE, and scholars have explored the spatial differentiation patterns and driving mechanisms of CEE with different emphases. However, there are still some unresolved analytical issues. On the one hand, there is a lack of research on CEE at the urban level as a spatial unit. In terms of research scale, most studies on CEE in China have been conducted from a macro perspective, such as industry level (Gao et al. 2021) and national or provincial level (Wang et al. 2023a, b; Zeng et al. 2019). With the coordinated development of regions, barriers between cities have been gradually broken, and factors of production flow more freely between neighboring cities, leading to a continuous reduction in the scale of spatial effects among regions. The analysis at the macro scale may not fully meet the requirements of the Chinese context (Wang and Huang 2019). Moreover, as cities are major sources of greenhouse gas emissions and low-carbon city construction is crucial for carbon reduction (Wen et al. 2022), the importance of studying carbon emissions at the city level is self-evident. In studies of influencing factors, many researchers utilize traditional econometric methods such as Tobit regression (Zhang and Xu 2022) and quantile regression (Xie et al. 2021) to uncover the determinants of urban CEE.

Summarizing previous research, it is evident that the study of urban CEE has made progress but still faces several limitations: Firstly, due to the lack of urban energy statistics data, most studies have focused on regional or national CEE, primarily emphasizing comparative analyses among different regions or countries. There is a notable scarcity of research on the urban-scale CEE. However, considering that cities are the largest contributors to energy consumption and greenhouse gas emissions, investigating their CEE is of paramount theoretical and practical significance for promoting low-carbon urban development and a sustainable economy. Secondly, the increasing flow of resources, elements, and collaborative communication within regions has led to spatial correlations in CEE. However, the specific characteristics of this spatial correlation require further exploration. Thirdly, in the analysis of influencing factors, traditional econometric methods often overlook the influence and effects of spatial factors. The lack of clarity regarding spatial influence pathways constrains the establishment of a coherent spatial analysis framework. There has been limited research expanding the boundaries of this field through the introduction of spatial econometric models.

Therefore, we aim to clarify the spatial driving effects of relevant factors on CEE and accurately reveal the specific characteristics of urban CEE changes. We take 42 cities in the three provinces of the middle reaches of the Yangtze River as the research units. Firstly, we use the index decomposition method to obtain the consumption of different fossil fuels in each city. Then, we apply the super-efficiency SBM with undesirable outputs to calculate the CEE from 2011 to 2019. We then use correlation analysis to examine the relationship between influencing factors and carbon emissions and the spatial agglomeration of urban CEE. Finally, we use the spatial Durbin model (SDM) to analyze the spatial spillover effects of urban CEE and its influencing factors. This study may have the following marginal contributions: Firstly, in terms of sample selection and research scale, conducting CEE studies at the urban level can yield more precise results and better align with the realities of spatial spillovers, thereby providing a reliable foundation for the construction of low-carbon cities. Secondly, at the theoretical level, we aim to construct a comprehensive impact indicator system to more comprehensively depict the spatial spillover pathways and mechanisms of CEE. Thirdly, we analyze the spatiotemporal evolution patterns of urban CEE in the study area, summarizing the spatial distribution, correlations, and clustering characteristics of urban CEE. Lastly, by integrating the results of influencing factors and spatial analysis, we present practical guidelines for promoting sustainable and

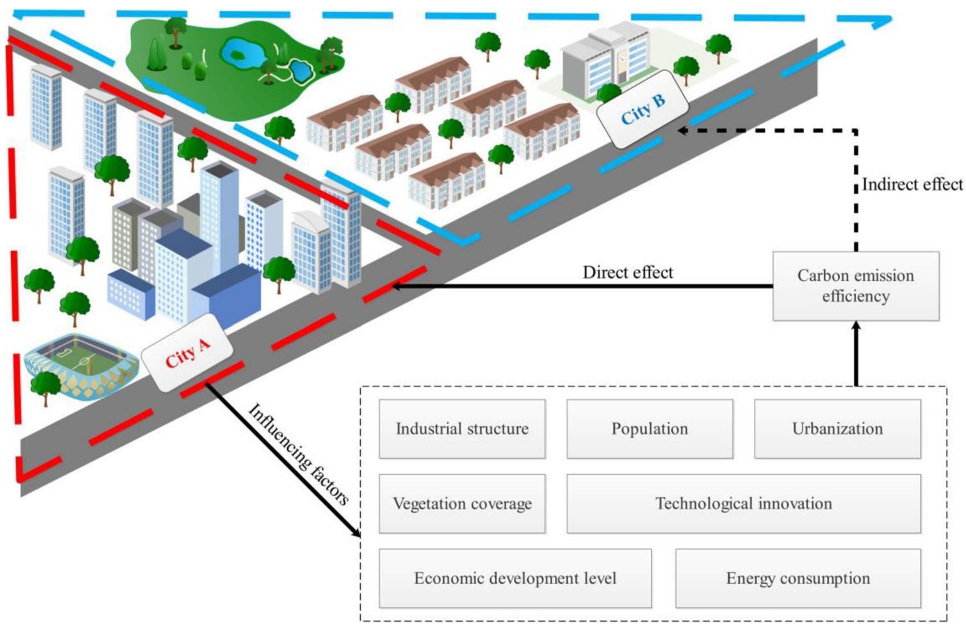


Fig. 1 Theoretical framework

low-carbon development in the entire research area and for different types of cities.

Theoretical framework

The spatial spillover effect is an important research object in the fields of regional economics and urban planning, which plays an important guiding role in formulating policies and planning urban development (Wu et al. 2022). The spillover effect refers to the impact of an economic or social behavior that extends beyond the area or group in which the behavior originated and spreads through certain channels to surrounding areas or groups. This diffusion effect may have positive or negative impacts on the surrounding areas (Qin et al. 2019; Yu et al. 2013).

Spatial spillover effects of CEE are typically influenced by multiple factors at different levels, such as the economy, environment, and society. Based on previous research, we can categorize the influencing factors of CEE into seven main categories. The first factor is industrial structure (Wang et al. 2019a). Adjustments in the industrial structure of a region can lead to the transfer of carbon emissions, which is one manifestation of spatial spillover effects. For example, certain regions may relocate high carbon-emitting industrial sectors to other areas, resulting in a reduction of carbon emissions in the local region but an increase in emissions in the receiving region. The second factor is urbanization (Zhang and Chen 2021). The accelerated pace of urbanization is accompanied by concentrated resource utilization and the diffusion of environmental pollution, affecting the CEE of the local region and adjacent areas. The third factor is population (Gong et al. 2022). Population growth and mobility can impact CEE among different regions through employment, transportation activities, and the provision of public services. The fourth factor is vegetation coverage (Wang et al. 2020a). Vegetation coverage reflects the land use structure. Increasing vegetation coverage appropriately is an effective measure for carbon reduction. Vegetation coverage influences the energy consumption performance of cities through photosynthesis and soil carbon storage. The fifth factor is technological innovation (Sun et al. 2023). Technological advancements contribute to improving energy efficiency, optimizing production methods, and promoting the innovation of low-carbon technologies. As technological innovation is disseminated and adopted, it affects carbon emissions in both the local region and surrounding areas. The sixth factor is the level of economic development (Sun and Huang 2020). When an economy reaches a certain stage of development, it triggers institutional changes, evolution in economic structure, and shifts in consumer attitudes, all of which impact CEE. The last factor is energy consumption (Guo et al. 2022). Increased energy consumption typically leads to a direct increase in carbon emissions, thereby influencing both the environment and CEE in cities and their surrounding regions.

To avoid potential biases when examining spatial spillover effects, we have incorporated the partial differentiation method, building upon Lesage's (2008) research, to decompose the spatial spillover effects of the SDM into three distinct components: direct effect, indirect effect, and total effect (Fig. 1). The direct effect represents the impact of influencing factors on the CEE of the local city, while the indirect effect signifies the influence of these factors on the

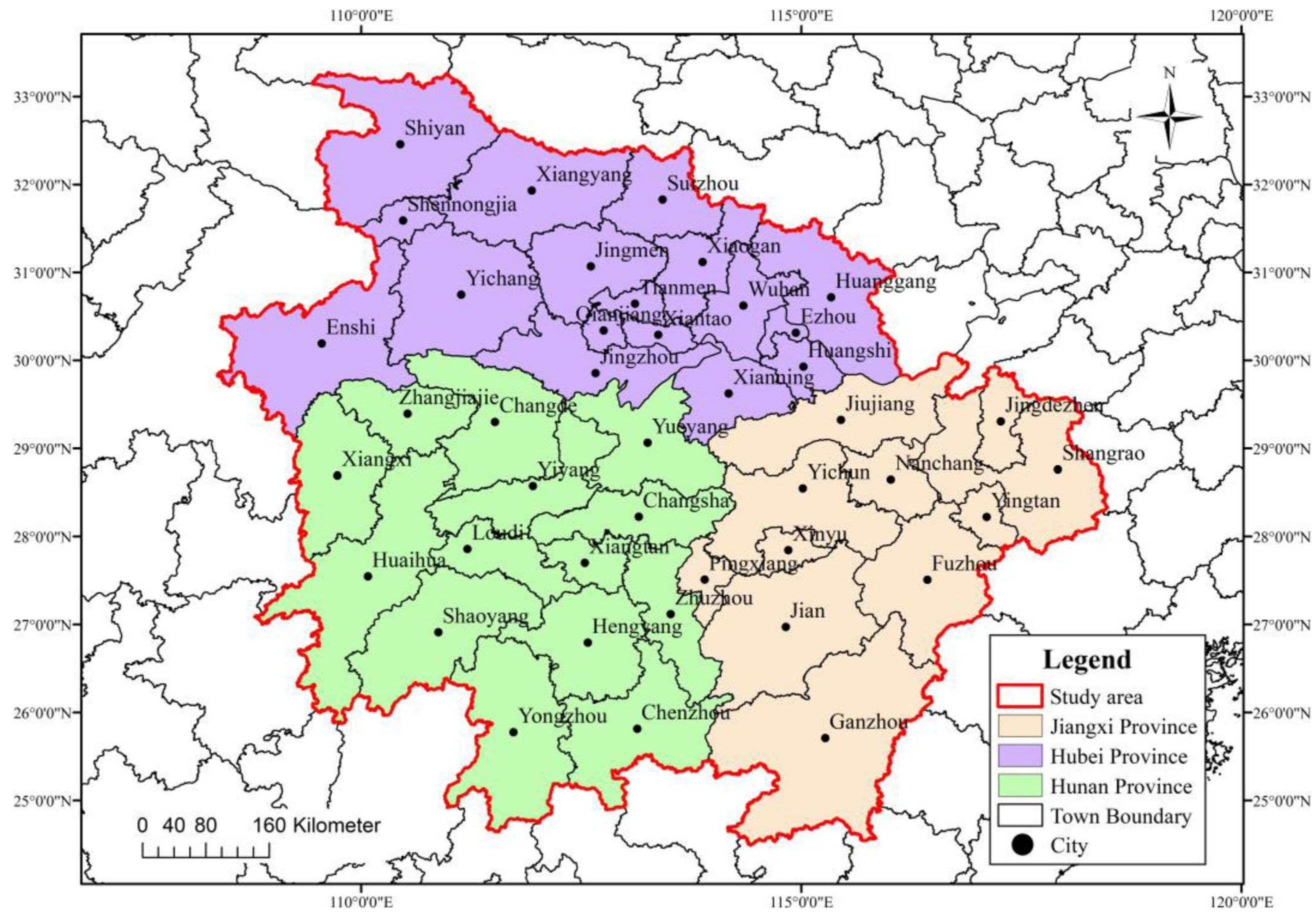


Fig. 2 The administrative map of the study area

CEE of surrounding cities. The total effect is the sum of the direct and indirect effects.

Data and methods

Research area

The research area of this study is the middle reaches of the Yangtze River, specifically the provinces of Hunan, Hubei, and Jiangxi (Fig. 2). Situated in central China, the middle reaches of the Yangtze River enjoy a favorable geographical location. The region has a well-developed transportation network comprising multiple railways, highways, major hub airports, and modern ports along the Yangtze River, holding a significant strategic position in the comprehensive national transportation system. The provinces of Hunan, Hubei, and Jiangxi share close cultural ties, interconnected by their landscapes, and have established extensive cooperation in key areas such as industrial development, social security, and infrastructure construction. This collaboration has laid a solid foundation for regional integration and development. Particularly in terms of ecological cooperation and environmental governance, the three provinces have demonstrated distinctive features. The Wuhan Metropolitan Area, the Changsha-Zhuzhou-Xiangtan Urban Agglomeration, the Poyang Lake Urban Agglomeration, the Dongting Lake Ecological Economic Zone, and the Comprehensive Reform Pilot Zone for Building a "Two-oriented Society" are all located in this region. The vast ecological space in the area necessitates collaborative efforts in ecological construction and shared responsibilities. Cities, as the concentrated hubs of human socioeconomic activities and carbon emissions, are considered the fundamental research units in this study. The spatial scope is determined by administrative boundaries and encompasses 42 cities, including prefecture-level cities, county-level cities under provincial jurisdiction, and autonomous prefectures.

Research methods

Index decomposition method

The most direct method for calculating carbon emissions is based on the energy consumption of cities. However, there

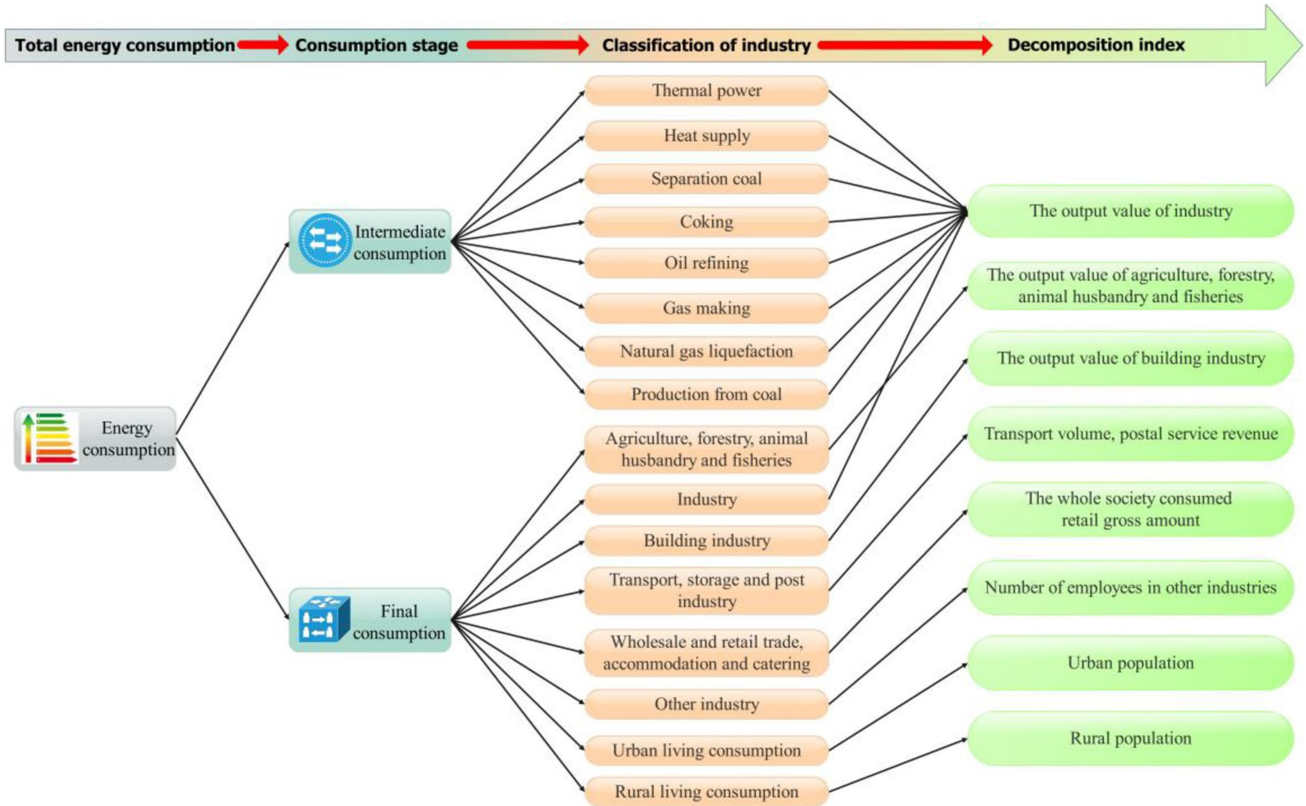


Fig. 3 Classification and decomposition index of provincial energy balance sheet

has been limited attention to carbon emissions at the city level because China's statistical authorities often only provide energy consumption data at the provincial level and for a few developed cities. Nevertheless, provincial-level energy balance sheets can be utilized for disaggregating energy consumption data at the city level using a top-down indicator decomposition method (Jing et al. 2019). This approach allows for the conversion of energy consumption into carbon emissions. Equations (1) and (2) below illustrate this process:

$$AD^{c}_{i,j} = AD^{p}_{i,j}a_j, \tag{1}$$

$$a_j = \frac{I^c_j}{I^p_j}, \tag{2}$$

where j represents the category of energy consumption, corresponding to the row j in the provincial-level energy balance sheet; $AD^c_{i,j}$ (10^4 t or 10^9 m^3) is the consumption of fossil fuels i in the industry j in the city; $AD^p_{i,j}$ (10^4 t or 10^9 m^3) is the consumption of fossil fuel i in the industry j in the province where the city is located; a_j is the distribution coefficient of industry j; I^c_j represents the value of the distribution index of industry j in a city; I^p_j represents the value of the distribution index of industry j in the province where a city is located.

The selection of distribution indicators requires a comprehensive consideration of representativeness, continuity, and correlation, as it determines the rationality and closeness of the linkages between cities and provinces. Based on the structure of the energy balance sheet and after excluding duplicated production processes, we have ultimately chosen the distribution indicators shown in Fig. 3.

After calculating the energy consumption, the direct carbon emissions generated by energy consumption within the jurisdiction boundaries of each city can be calculated using the following formula:

$$CE^c = \sum_{i=1}^{27} AD^c_i EF_i \tag{3}$$

where CE^c (10^4 t) is the total energy consumption of the city; i is the types of fossil fuels; AD^c_i (10^4 t or 10^9 m^3) is the consumption of fossil fuel i; EF_i is the emission factor of fossil fuel i, determined based on the recommended values from Guidelines for the Preparation of Provincial Greenhouse Gas Inventories.

Table 1 The indicators of carbon emission efficiency

Indicator types	Indicators	Variables and unit
Input indicators	Manpower	Employed population (10^4)
	Physical resources	Energy consumption (10^4 t of standard coal)
	Financial resources	Fixed asset investment (10^8 yuan)
Output indicators	GDP	GDP (10^8 yuan)
	Carbon emissions	Carbon emissions (10^4 t)

Super-efficiency slack-based model

Data envelopment analysis (DEA) is a non-parametric analysis method used to evaluate the relative efficiency of decision-making units (DMUs) based on their input–output relationships (Wang et al. 2020b). DEA has become a mainstream technical tool for efficiency evaluation due to its advantages, such as not requiring assumptions about functional relationships, non-subjective weighting, and the ability to analyze inefficient factors of DMUs. However, traditional DEA methods have shown two limitations in their application. Firstly, when the efficiency values of multiple DMUs are all equal to 1, further measurement and evaluation of their efficiency cannot be conducted. Secondly, traditional methods do not consider the slackness in input–output, leading to deviations between actual and theoretical values in efficiency measurement. To improve the traditional DEA model, Tone (2001) integrated the super-efficiency model with the SBM (slack-based measure) model, proposing the super-efficiency SBM model. This model considers both the slack variables in input–output and provides more accurate efficiency evaluation results, while also addressing the problem of comparing and ranking multiple efficient units. In the process of economic production, inputs such as labor, capital, and energy not only yield industrial products but also generate a byproduct, CO_2 emissions, which are considered as unexpected outputs. This modeling approach, due to its consideration of these unexpected outputs during the production process, aligns better with real-world situations. As a result, it has found widespread application in research related to carbon emission efficiency (Fang et al. 2022), ecological efficiency (Wang et al. 2023a, b), and energy efficiency (Zhang et al. 2020b) measurements. The calculation principle of the super-efficiency SBM model assumes the presence of n decision-making units, each consisting of inputs m, expected outputs r_1, and undesired outputs r_2. We assume that the DMUs in the super-efficiency SBM model are all efficient. The calculation formula is as follows:

$$\mathrm{Min}\varphi = \frac{1/m \times \sum_{i=1}^{m} \left(\overline{x} / x_{ik} \right)}{1 \Big/ \left(r_1 + r_2\right) \times \left(\sum_{s=1}^{r_1} \overline{y^d} \Big/ y_{sk}^d + \sum_{q=1}^{r_2} \overline{y^u} \Big/ y_{qk}^u \right)} \tag{4}$$

$$\begin{cases} \overline{x} \geq \sum_{j=1,\neq k}^{n} x_{ij}\lambda_j; i = 1, \cdots, m \\ \overline{y^d} \leq \sum_{j=1,\neq k}^{n} y_{sj}^d \lambda_j; s = 1, \cdots, r_1 \\ \overline{y^d} \geq \sum_{j=1,\neq k}^{n} y_{qj}^u \lambda_j; q = 1, \cdots, r_2 \\ \lambda_j \geq 0; j = 1, \cdots, n; j \neq 0 \\ \overline{x} \geq x_k; k = 1, \cdots, m \\ \overline{y^d} \leq y_k^d; q = 1, \cdots, r_1 \\ \overline{y^u} \geq y_k^u; u = 1, \cdots, r_2 \end{cases} \tag{5}$$

where φ is the CEE; i represents the number of inputs; s is the number of expected outputs; q is the number of undesired outputs; $\overline{x}$ is the slack variable of inputs; $\overline{y^d}$ is the slack variable of expected outputs; $\overline{y^u}$ is the slack variable of undesired outputs; x_{ik} is the optimal input i in the decision unit k improved by the slack variable; y_{sk}^d is the expected output s in the decision unit k improved by the slack variable; y_{qk}^u is the undesired output q in the decision unit k improved by the slack variable; λ_j is the weighting vector.

When applying the super-efficiency SBM model to evaluate the efficiency of decision-making units, it is required that the number of decision-making units is at least twice the number of input–output indicators. Based on previous research (Liu et al. 2018), we have constructed an evaluation index system for urban carbon emission efficiency, as shown in Table 1.

Spatial autocorrelation analysis

Spatial autocorrelation analysis is a statistical method used to study geographical spatial data. It aims to evaluate the similarity and level of association among data values in geographic space, while also revealing spatial dependence and spatial heterogeneity phenomena in geographical data. This method takes into account the influence of geographical location to determine whether there is clustering or dispersion of CEE in space. Spatial autocorrelation analysis includes global spatial autocorrelation and local spatial autocorrelation (Zhou et al. 2022). Global spatial autocorrelation is employed to analyze the level of correlation exhibited by spatial data within the entire spatiotemporal system. It examines whether neighboring regions throughout the study exhibit spatial positive correlation, negative correlation, or mutual independence (Lin et al. 2020). Therefore, we

Table 2 Independent variables and descriptive statistics

Independent variables	Descriptions	Mean	Std. Dev	Min	Max
Ind	The proportion of the added value of the secondary industry to regional GDP (%)	0.476	0.091	0.147	0.793
Urb	The proportion of the urban population to the total population (%)	0.495	0.130	0.130	0.796
Pop	Population density (1000 people/km^2)	0.364	0.208	0.024	1.301
Gre	Green coverage rate (%)	0.404	0.066	0.105	0.709
Pat	Number of patent applications (10,000)	0.377	0.744	0.002	7.591
Eco	GDP per capita (100,000 yuan)	0.452	0.263	0.104	1.790
Ene	Energy consumption per unit of GDP (ton of steam coal equivalent/10,000 yuan)	0.734	0.263	0.145	1.891

Ind industrial structure, *Urb* urbanization, *Pop* population, *Gre* vegetation coverage, *Pat* technological, *Eco* economic development level, *Ene* energy consumption

employ global spatial autocorrelation to analyze the spatial association of CEE across the entire study area, and it is calculated as follows:

$$I = \frac{n\sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij}(x_i - \overline{x})(x_j - \overline{x})}{\sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij}\sum_{i=1}^{n}(x_i - \overline{x})^2}, \tag{6}$$

where I is global Moran's I ($I = 0$ indicating no spatial correlation, $I > 0$ indicating a positive spatial correlation, $I < 0$ indicating a negative spatial correlation); x_i and x_j represent the CEE of cities i and j respectively; $\overline{x}$ represents the average CEE of cities in the study area; W_{ij} is the spatial weight matrix based on geographic proximity; n represents the number of cities.

Global spatial autocorrelation cannot indicate the specific locations of spatial clustering, and further analysis is needed using local autocorrelation tools. Local Moran's index measures spatial correlation by assessing the similarity between each geographic unit (typically a point, region, or area) and its neighboring geographic units. This index can be used to identify local clusters or spatial dispersion in geographical space (Chuai et al. 2012). Based on the calculation results of local Moran's I, four types of spatial correlation patterns can be identified: High-High aggregation, High-Low aggregation, Low–High aggregation, and Low-Low aggregation. The expressions for these patterns are as follows:

$$I_i = \frac{n(x_i - \overline{x})\sum_{j=1}^{n} W_{ij}(x_i - \overline{x})}{\sum_i (x_i - \overline{x})^2}, \tag{7}$$

where I_i is local Moran's I in spatial unit i.

Spatial Durbin model

Based on the theoretical analysis above, the selected independent variables and their descriptive statistical results of 378 observations are shown in Table 2. The dependent variable is the urban CEE. We need to further characterize the impact mechanism of influencing factors on the spatial spillover effects of CEE. Traditional econometric methods often struggle to capture cross-regional spatial spillover effects (Zhou et al. 2019a, b). Therefore, there is a need to construct spatial econometric models to obtain precise results (Huang and Tian 2023). The spatial Durbin model is one widely applied spatial statistical model used to analyze causality and interdependence in spatial data (Zhang et al. 2022b). This model extends the traditional multiple regression model to account for spatial correlation and spatial lag effects. Its fundamental assumption is that the observations in one geographical area may be influenced by the observations in neighboring areas, making spatial interdependence a key feature of this model. Moreover, the SDM considers both the spatial correlation between the dependent variable and the independent variables. It suggests that the dependent variable of a spatial unit is not only influenced by its own independent variables but also by the neighboring units' dependent and independent variables (Cao et al. 2022). After conducting some tests, we used the SDM model to explore the impact mechanism of urban CEE and its direct and indirect spatial spillover effects. The calculation formula is as follows:

$$y = \beta_0 + \alpha w_{F_{ij}} y\prime + \sum_{i=q}^{n} \beta_i x_i + \sum_{j=1}^{n} w_{F_{ij}} \beta_j x_j + \varepsilon \tag{8}$$

where y represents CEE; $y\prime$ represents the CEE of neighboring city units; α represents the spatial regression coefficient of CEE; β_0 represents the intercept term; β represents the regression coefficient of the independent variable; x represents the independent variable; $w_{F_{ij}}$ is the weight matrix that embeds the spatial adjacency relationship of city units; ε is the error term following a normal distribution.

Data sources

In this study, the period examined spans from 2011 to 2019. The energy consumption data is sourced from the China

Table 3 Urban CEE of Hunan, Hubei, and Jiangxi provinces from 2011 to 2019

Cities	2011	2015	2019	Cities	2011	2015	2019
Wuhan	0.481	0.659	1.029	Shaoyang	0.394	0.294	0.358
Huangshi	0.371	0.341	0.428	Yueyang	0.571	0.447	0.464
Shiyan	0.360	0.354	0.430	Changde	1.063	0.632	0.667
Jingzhou	0.336	0.283	0.382	Zhangjiajie	0.767	0.883	0.780
Yichang	0.504	0.439	0.825	Yiyang	0.501	0.361	0.370
Xiangyang	0.518	0.396	0.461	Chenzhou	0.394	0.329	0.356
Ezhou	0.362	0.351	0.444	Yongzhou	0.457	0.381	0.410
Jingmen	0.366	0.328	0.371	Huaihua	0.504	0.512	0.484
Xiaogan	0.310	0.273	0.358	Loudi	0.476	0.401	0.359
Huanggang	0.349	0.295	0.387	Xiangxi	0.642	0.549	0.865
Xianning	0.305	0.282	0.342	Nanchang	0.439	0.406	0.435
Suizhou	0.337	0.303	0.355	Jingdezhen	0.431	0.391	0.420
Enshi	0.544	0.529	1.133	Pingxiang	0.349	0.315	0.238
Xiantao	0.515	0.430	0.493	Jiujiang	0.360	0.280	0.357
Tianmen	0.724	0.352	0.437	Xinyu	0.416	0.445	0.388
Qianjiang	0.321	0.410	0.533	Yingtan	0.332	0.325	0.385
Shennongjia	0.294	0.291	0.395	Ganzhou	0.441	0.325	0.491
Changsha	0.591	0.609	0.682	Jian	0.329	0.275	0.321
Zhuzhou	0.529	0.403	0.431	Yichun	0.391	0.306	0.426
Xiangtan	0.420	0.355	0.392	Fuzhou	1.209	0.340	0.384
Hengyang	0.551	0.508	0.507	Shangrao	0.395	0.325	0.353

Due to space limitations, only data for the years 2011, 2015, and 2019 are presented. Complete data can be found in the Supplementary Materials

Energy Statistical Yearbook (2012–2020) (CESY 2020). Socioeconomic data for each city is obtained from the statistical yearbooks of Hubei Province, Hunan Province, and Jiangxi Province. Employment data is sourced from the China City Statistical Yearbook (2012–2020) (CCSY 2020). Patent data is acquired from a professional patent search engine.[2]

Results

CEE and spatial–temporal evolution of the three provinces

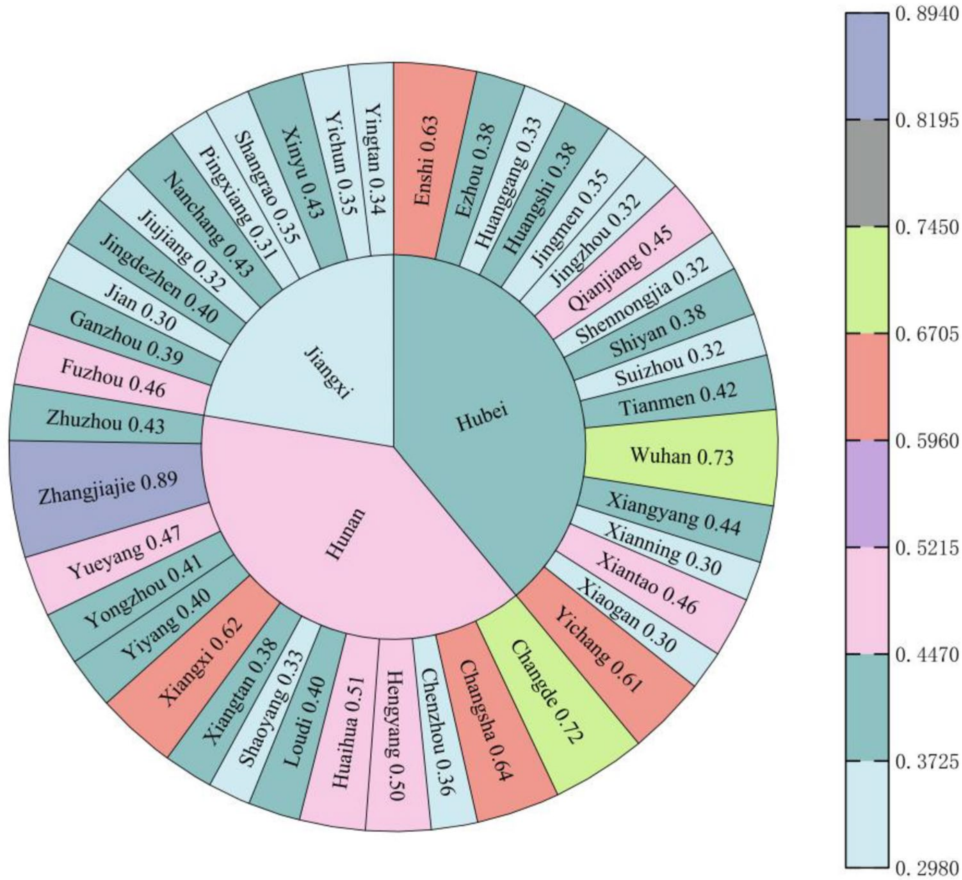
The input and output indicators of 42 cities in the middle reaches of the Yangtze River were calculated using the super-efficiency SBM model, and the CEE for the years 2011 to 2019 was obtained. The results are shown in Table 3.

Figure 4 presents the average CEE of each city from 2011 to 2019. The results indicate that there is minimal variation among cities in Jiangxi Province, with a close average CEE. The gap in CEE between cities in Jiangxi Province is the smallest, while there is significant variation in CEE among cities in Hunan and Hubei provinces. Zhangjiajie, Wuhan, Changde, Changsha, Enshi, Xiangxi, and Yichang exhibit significantly higher CEE compared to other cities in the study area and represent the region with the most promising CEE trends. The CEE in Jingzhou, Shennongjia, Jiujiang, Pingxiang, Xiaogan, Xianning, and Jian are all below 0.320, making them key areas that need to address carbon emission issues.

To further examine the spatial pattern differences in urban CEE within the study area, we employed the natural breaks method in ArcGIS software to categorize CEE into four classes for each year (Fig. 5). Analyzing the spatiotemporal evolution of CEE, we observed an overarching spatial pattern characterized by lower efficiency in the eastern and northern regions, contrasted with higher efficiency in the western regions. Specifically, looking at the evolution of CEE over time, we noted that in 2011, regions with high CEE were limited, with most areas exhibiting lower or low CEE. However, by 2014, there was a noticeable uptick in CEE in many cities, with some high-efficiency cities clustering in the western region. Subsequently, there was a general downward trend until 2017, with some fluctuations in 2018 and 2019. Ultimately, a spatial pattern emerged, featuring a northern region with higher CEE, dominated by cities like Enshi, Xiangxi, Zhangjiajie, Yichang, and Changde. Furthermore, developed cities with high CEE, such as Wuhan

[2] http://www2.soopat.com/

Fig. 4 Average value of urban carbon emission efficiency



and Changsha, also intermingle with cities characterized by relatively low and low carbon emissions.

The CEE not only exhibits differences in spatial patterns but also has evolutionary patterns in time series. Figure 6 provides a clear reflection of the degree of CEE changes for each city from 2011 to 2019. The box plot reveals significant variations in CEE among different provinces and cities. At the provincial level, Jiangxi Province exhibits a noticeably more stable evolution of CEE compared to Hubei and Hunan provinces. On the city level, Wuhan, Yichang, and Zhangjiajie display larger variances, indicating less stability in their CEE and substantial differences between different years. In contrast, cities such as Huangshi, Jingmen, Xianning, Suizhou, and Shangrao show smaller variances, reflecting the persistent inefficiency in carbon emission throughout the years.

Spatial correlation characteristics of carbon emission efficiency

According to the global spatial autocorrelation analysis (Table 4), the results indicate that global Moran's index for the years 2012 to 2019 is positive and statistically significant. This suggests a significant spatial autocorrelation in CEE among cities, demonstrating a clear spatial clustering pattern. Global Moran's index shows a decreasing trend from 2012 to 2017, followed by a gradual increase until 2019, overall conforming to a pattern of initial decline and subsequent rise.

To further characterize the spatial patterns of CEE among cities and their neighboring cities, we conducted a local spatial autocorrelation analysis to examine the explicit spatial morphology of CEE (Fig. 7). Overall, global Moran's *I* for CEE of cities in the study area was all greater than 0, indicating a positive spatial autocorrelation and a pattern of "small clustering, large dispersion" in CEE. A significant number of points fall in the third quadrant, indicating a clustering pattern of low-efficiency cities with their neighboring low-efficiency cities. This suggests that low-efficiency cities tend to cluster together in the study area. On the other hand, there are relatively few points in the first quadrant, indicating a limited occurrence of spatial clustering between high-efficiency cities and their neighboring high-efficiency cities. We can observe several changes from Fig. 7: Firstly, the number of cities falling into the first quadrant (High-High aggregation) remains relatively stable each year, accounting for approximately 20% of the total. Cities in this quadrant, represented by regions such as Xiangxi, Enshi, Zhangjiajie, Changde, and Yichang on the border of

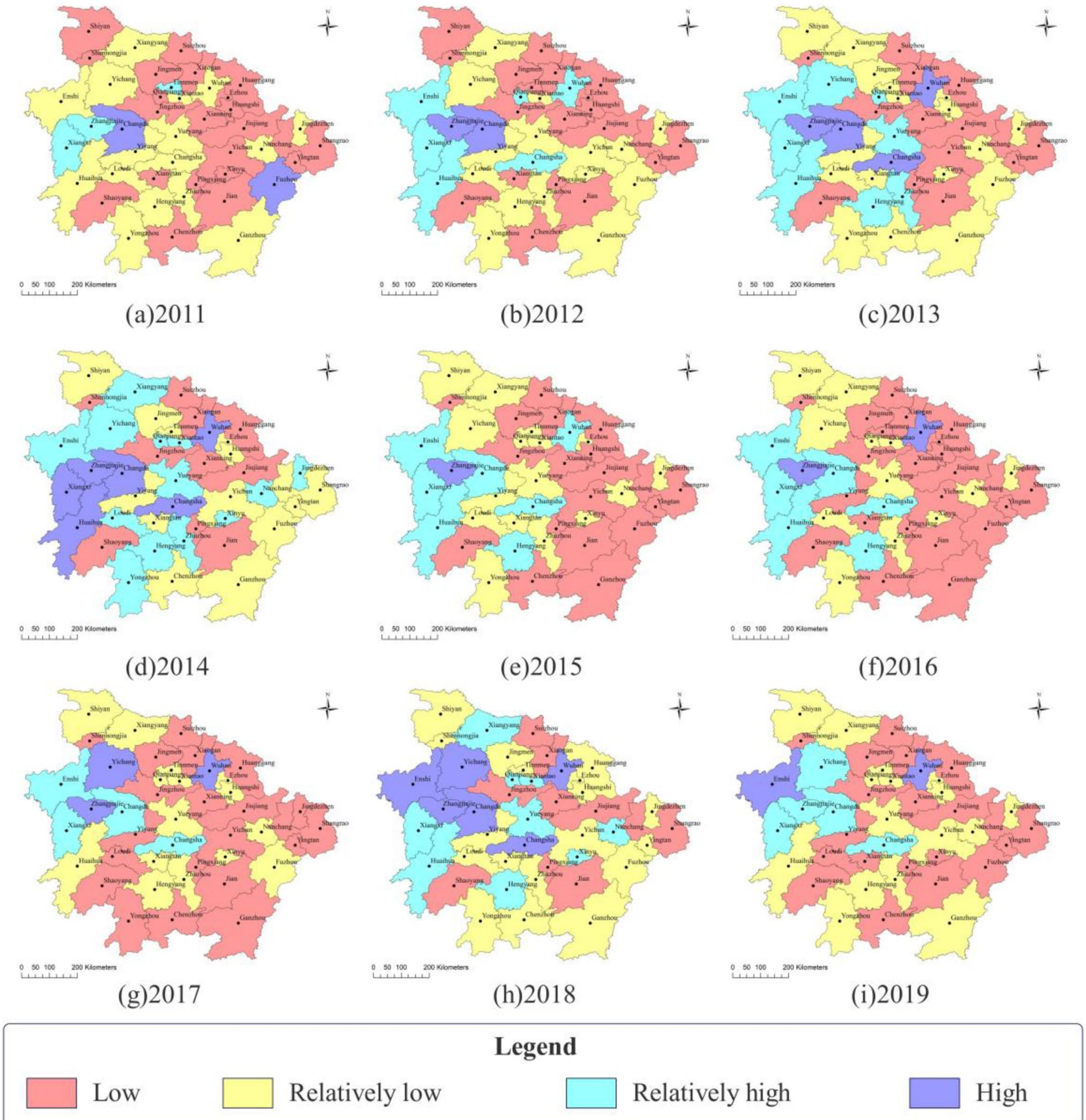


Fig. 5 Distribution pattern of carbon emission efficiency in the study area

Hunan and Hubei provinces, are all within the watershed of the important Yangtze River tributary, the Li River. In recent years, these cities have focused on collaborative governance in the ecological protection areas of the Yangtze River Basin, achieving commendable results in environmental management and contributing to improved CEE. Secondly, the proportion of cities falling into the second quadrant (Low–High aggregation) shows a trend of initial decline followed by an increase, with percentages of 0.26, 0.17, and 0.21 in 2011, 2015, and 2019, respectively. Representative cities in this quadrant include Yiyang, Xiangtan, Ezhou, Huanggang, and Yingtan. These cities have relatively low CEE themselves but are surrounded by cities with higher CEE. The reason for cities falling into this quadrant is primarily their proximity to provincial capitals but having significantly different CEE levels. Thirdly, the proportion of cities in the third quadrant (Low-Low aggregation) is

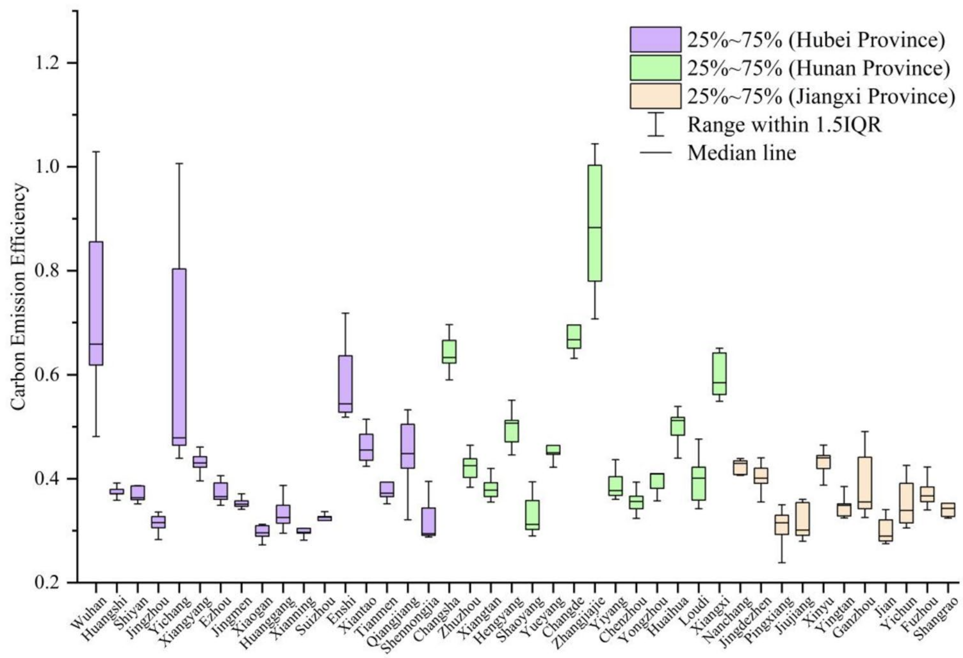


Fig. 6 Box diagram of urban carbon emission efficiency in Hunan, Hubei, and Jiangxi provinces

Table 4 Global Moran's index from 2011 to 2019

Indicators	2011	2012	2013	2014	2015	2016	2017	2018	2019
I	0.008	0.283	0.252	0.211	0.203	0.147	0.107	0.156	0.228
Z-score	0.385	3.716	3.214	2.606	2.634	2.021	1.535	2.067	2.904
P value	0.350	0.000	0.001	0.005	0.004	0.022	0.062	0.019	0.002

increasing annually. The percentage of cities in this quadrant was 0.33, 0.47, and 0.50 in 2011, 2015, and 2019, respectively, encompassing many underdeveloped cities within the study area. These cities may be relatively lacking in balancing the dual objectives of environmental protection and economic development, with more emphasis placed on economic development. Consequently, their governance effectiveness in carbon emission control is relatively low. Fourthly, the proportion of cities in the fourth quadrant (High-Low aggregation) is decreasing over the years, with percentages of 0.21, 0.17, and 0.12 in 2011, 2015, and 2019, respectively. Representative cities in this quadrant include Wuhan, Changsha, Zhuzhou, Yueyang, and Nanchang, which are relatively developed cities within the study area. These cities have higher CEE themselves but are surrounded by cities with lower CEE. This indicates that while these cities have relatively high environmental governance levels, their radiating influence is limited.

The spatial spillover effect of carbon emission efficiency

Model test

The test for spatial correlation indicates a strong spatial dependence in CEE. To further analyze the spatial spillover effects of CEE, we conducted tests to identify the appropriate spatial effects model (Table 5). Firstly, the LM and Robust LM statistics pass the significance tests at 1% and 5% levels, respectively, rejecting the Ordinary Least Squares model. Secondly, the Hausman test has a *P* value below 0.05, rejecting the random effects model and indicating the fixed effects model should be chosen. Lastly, the LR test and Wald test both pass the significance tests at a 1% level, suggesting that the SDM is the optimal model and not degrading into a spatial error model or spatial lag model.

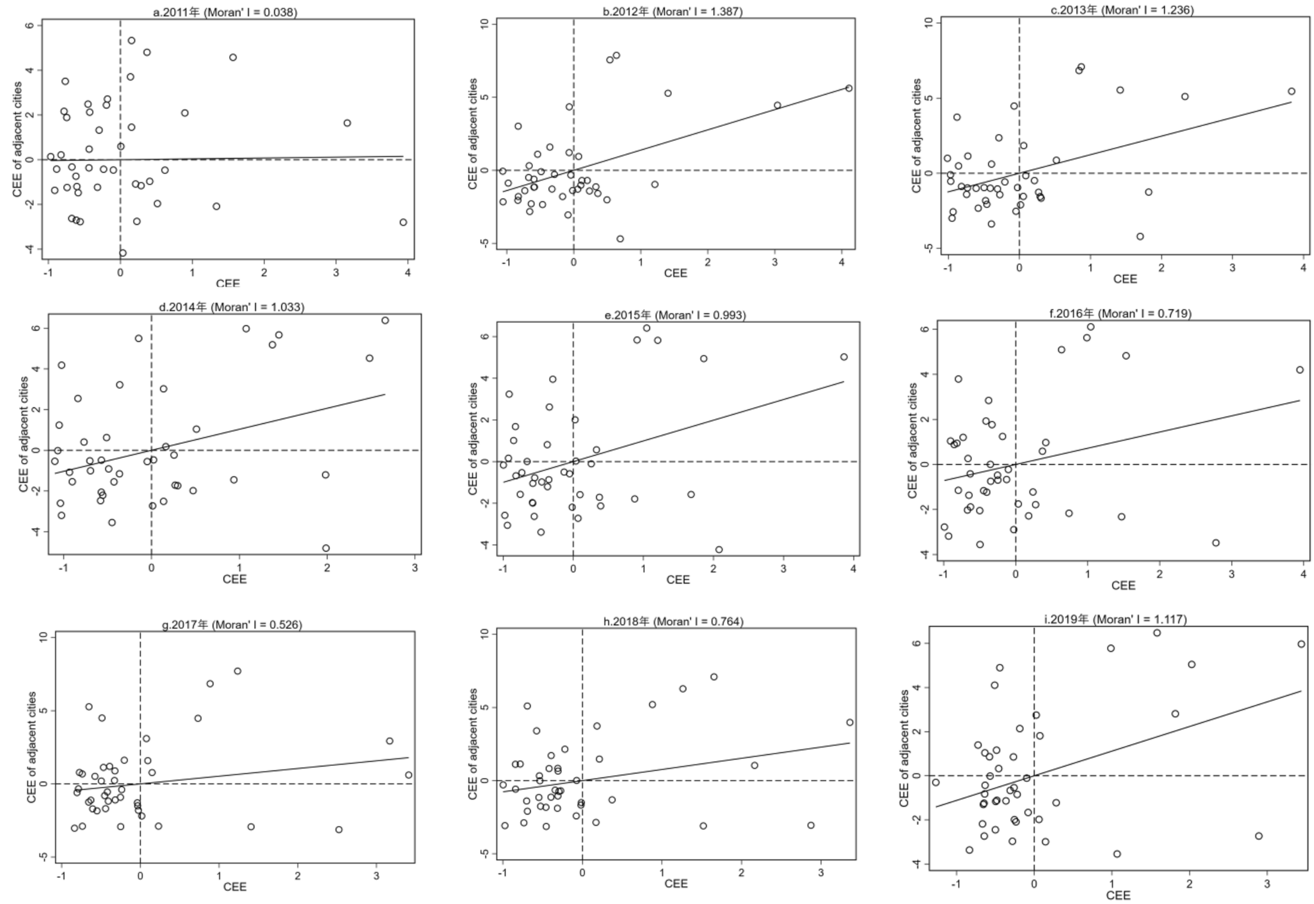


Fig. 7 Moran scatter diagram of urban carbon emission efficiency in Hunan, Hubei, and Jiangxi from 2011 to 2019

Table 5 Test results of the spatial panel model

Testing method	Statistics	*P* value
LM-spatial lag	71.16	0.000
Robust LM-spatial lag	11.01	0.001
LM-spatial error	62.05	0.000
Robust LM-spatial error	1.89	0.039
Hausman test	28.07	0.021
LR-spatial lag	82.51	0.000
LR-spatial error	87.54	0.000
Wald-spatial lag	27.45	0.000
Wald-spatial error	28.27	0.000

The results and analysis of spatial spillover effects

Due to the Hausman test indicating the superiority of the fixed effects model, we employed maximum likelihood estimation to estimate the spatial Durbin model with both time and space fixed effects, as shown in Table 6. The coefficients for urbanization, technological innovation, and economic development level are positive and pass significance tests at the 5% level or higher, indicating that these factors are conducive to promoting urban carbon emission efficiency. Conversely, the coefficients for industrial structure, population, and energy consumption pass significance tests at the 10% level or higher, suggesting that these factors have a negative impact on improving urban carbon emission efficiency. Furthermore, in the spatial lag terms, urbanization, technological innovation, and economic development level pass significance tests at the 10% level or higher, and their elasticity coefficients are positive. This implies that these explanatory variables not only contribute to improving carbon emission efficiency within the city itself but also facilitate the enhancement of carbon emission efficiency in neighboring cities. On the other hand, industrial structure, population, and energy consumption have a negative impact on the improvement of carbon emission efficiency in both the city itself and neighboring cities.

Due to the inclusion of spatial lag terms for both the independent and dependent variables in the SDM model, the estimation of spatial spillover effects cannot be simply based on the regression coefficients of each independent variable. This is because the limitations of regression

Table 6 Regression results of spatial Durbin model under fixed effects

Variables	Main	Wx
Ind	-0.270^{**} (0.107)	-1.106^{***} (0.193)
Urb	0.013^{**} (0.061)	0.068^{*} (0.113)
Pop	-0.002^{*} (0.043)	-0.087^{*} (0.071)
Gre	0.263 (0.088)	0.129 (0.156)
Pat	0.004^{***} (0.013)	0.149^{***} (0.030)
Eco	0.374^{***} (0.045)	0.202^{*} (0.106)
Ene	-0.246^{***} (0.028)	-0.061^{**} (0.049)

Main represents the regression coefficients, indicating the impact of explanatory variables on the dependent variable within the city itself. Wx represents the spatial lag term, indicating the impact of explanatory variables from neighboring cities on the dependent variable within the city. The value of Rho (spatial autocorrelation coefficient) is 0.228 and significant at the 1% level. The value of sigma2_e (variance) is 0.008 and significant at the 1% level. The values within brackets below the coefficients are standard deviations. *, **, and *** indicate 10%, 5%, and 1% significance levels, respectively

Table 7 The decomposition of spatial effect of influencing factors of carbon emission efficiency

Variables	Direct effect	Indirect effect	Overall effect
Ind	-0.606^{***} (0.107)	-0.252^{***} (0.071)	-0.858^{***} (0.155)
Urb	-0.082^{***} (0.063)	-0.034^{***} (0.029)	-0.117^{***} (0.090)
Pop	-0.072^{*} (0.038)	-0.030^{*} (0.018)	-0.102^{*} (0.054)
Gre	0.196 (0.091)	0.083 (0.045)	0.278 (0.132)
Pat	0.007^{***} (0.013)	0.003^{***} (0.006)	0.010^{***} (0.019)
Eco	0.401^{***} (0.047)	0.168^{***} (0.047)	0.569^{***} (0.080)
Ene	-0.241^{***} (0.029)	-0.100^{***} (0.026)	-0.341^{***} (0.043)

The values within brackets below the coefficients are standard deviations. *, **, and *** indicate 10%, 5%, and 1% significance levels, respectively

coefficients lie in their inability to effectively reflect the extent of influence of the independent variables on the dependent variable (Bu et al. 2021). Therefore, we employ a partial differentiation method to decompose the spatial effects into direct and indirect effects in order to assess the degree of influence and spillover effects of the independent variables. The results are shown in Table 7.

The industrial structure has a negative effect on CEE. Both the direct effect and indirect effect are significantly negative, indicating that an increase in the proportion of the secondary industry has a restraining effect on both local and neighboring cities' CEE. Specifically, for every 1% decrease in the proportion of the secondary industry, the CEE of the local city improves by 0.606%, and the CEE of neighboring cities increases by 0.252%. Considering the current development status of China's industries, the secondary industry is mostly composed of high-energy-consuming and high-emission sectors. It consistently holds the largest share in total carbon emissions. Insufficient application of green and low-carbon technologies in industrialization greatly reduces CEE (Wang et al. 2019b). At the same time, cross-regional industrial cooperation and industrial transfer may also lead to negative spillover effects between neighboring cities. Therefore, it is necessary to take into account the current situation of each city and gradually phase out high-pollution industries, achieve industrial upgrading and transformation, and optimize low-carbon and green industrial chains. This will ultimately improve the overall CEE of the region.

The increase in urbanization has a negative impact on CEE, as indicated by the significant results of both the direct and indirect effects at a 1% level of significance. The elasticity coefficients of the direct and indirect effects are −0.082 and −0.034, respectively. This suggests that holding other factors constant, for every 1% increase in the urbanization rate, the CEE of the local city and neighboring cities will reduce by 0.082% and 0.034%, respectively. There are several possible reasons for this. On the one hand, urbanization drives the construction and use of infrastructure such as housing, entertainment, education, healthcare, and transportation, leading to increased energy consumption (Zhang and Chen 2021) and a reduction in the local area's CEE. On the other hand, the impact of urbanization is not confined to the city itself but also influences neighboring cities through spillover effects, stimulating production and consumption activities (Liu and Liu 2019). Consequently, this leads to increased energy demand and carbon emissions in the surrounding areas.

Population exhibited a negative direct effect and indirect effect on CEE at a 10% level of significance. This means that for every 1% increase in population density, the CEE of the city and neighboring cities will decrease by 0.072% and 0.030%, respectively. Previous studies have indicated that population agglomeration is beneficial for land-intensive use and efficient resource allocation, thereby improving CEE, but only within a certain threshold range. It is evident that in the rapid urbanization process of the three provinces in the middle reaches of the Yangtze River, some cities may face the issue of excessive population agglomeration, leading to increased burdens on public services and infrastructure, thereby reducing CEE (Chen et al. 2022).

Technological innovation has a positive direct effect and indirect effect on CEE, as indicated by the significant results at a 1% level of significance. Holding other conditions constant, for every 1% increase in the number of patent applications, the CEE of the local city and neighboring cities will improve by 0.007% and 0.003%, respectively. The number of patent applications serves as a measure of innovation achievements and is an important indicator of technological innovation and development. The positive impact of technological innovation on reducing CEE in the local city is significant. Additionally, the spatial spillover effect generated by technological innovation also plays a significant role in improving the CEE of neighboring cities. This is mainly due to the strong externality of technological innovation (Fu et al. 2022). The improvement in urban technological innovation capacity facilitates the acceleration of technological innovation in associated cities, thereby enhancing the CEE of neighboring cities.

The economic development level has a positive impact on CEE. The coefficients for its direct and indirect effects are 0.247 and 0.164, respectively, and both pass the significance test at the 1% level. This means that when other conditions remain constant, a 1% increase in the level of economic development will lead to a 0.401% and 0.168% improvement in CEE for the city and neighboring cities, respectively. With the advancement of economic development, there is increased market activity and resource flow between cities. As the CEE of key cities improves, it may indirectly drive the improvement of CEE in neighboring cities through the industrial chain and cooperation networks (Zhang et al. 2022c).

Energy consumption has both direct and indirect negative effects on CEE, both of which pass the significance test at the 1% level. The results indicate that for every 1% increase in energy consumption, the CEE of the city and neighboring cities will decrease by 0.241% and 0.100%, respectively. This may be because when the energy consumption of a city increases, it requires a greater energy supply. The energy supply chain often spans different regions (Wang and Chen 2016), which may lead to the mobilization of energy from other cities, thereby causing a reduction in the CEE of both the city and neighboring cities.

Furthermore, vegetation coverage did not pass the significance test. Vegetation coverage demonstrated a positive direct effect and indirect effect on CEE. This indicates that although vegetation coverage reflects the level of greening investment in each city and can improve CEE to some extent, the improvement is not significant.

Discussion

Comparison of model applications

In this study, we employed the SDM to analyze the influencing factors of urban CEE. To ensure the comprehensiveness and reliability of our analysis, it was necessary to compare our model with other approaches. In the broader context of previous research, the study of regional CEE and its influencing factors can be categorized into two main types: non-spatial econometric models and spatial econometric models. Non-spatial econometric models are typically used in studies at a larger spatial scale, such as city clusters (Zhang et al. 2020a), provinces (Zeng et al. 2019; Sun and Huang 2022), and countries (Wang et al. 2022). These studies typically employ models such as the Tobit regression model, the Pearson correlation test, and the generalized moment method to analyze the relationship or correlation between CEE and its influencing factors at an overall level. However, these models do not consider spatial dependency between regions, meaning they cannot capture the interdependence between regions, which can be important in CEE studies since the policies or actions of one region can affect the carbon emissions of neighboring regions.

The spatial econometric model is more suitable for studying carbon emission efficiency at the city level. Spatial econometric models are better suited for studying carbon emission efficiency at the urban level. Due to variations in research objectives and study subjects, the choice of spatial econometric models in previous research studies has also differed. These models have varying applicability based on their underlying assumptions. For instance, the spatial error model assumes that interregional interactions are captured through error terms, and spatial spillover effects result from random shocks (Chu et al. 2022). The spatial lag model takes into account the impact of neighboring regions' dependent variables on the dependent variable of the focal study area (Li et al. 2018). The spatial Markov model, on the other hand, is primarily used to describe and predict spatial state transition processes (Tang et al. 2021), rather than directly analyzing the factors influencing CEE. In other words, it focuses on how the CEE of a geographical area transitions from one state to another.

In our study, the spatial Durbin model proved to be the most suitable model. From a data testing perspective, we passed the LR test and Wald test, rejecting the assumptions of spatial lag model and spatial error model. Furthermore, SDM can incorporate geographical proximity weight matrices, providing a more comprehensive explanation of the spatial effect transmission mechanisms in CEE within collaborative development regions like our study area.

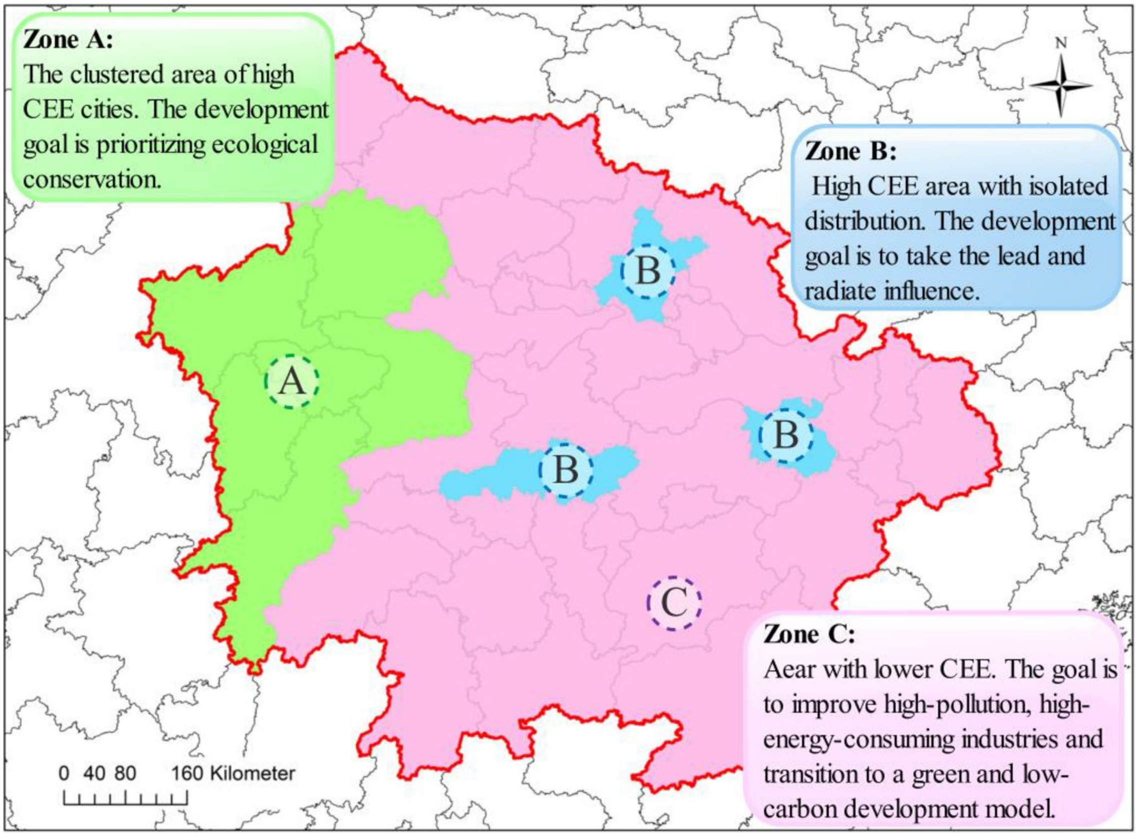


Fig. 8 Differentiated development goals in zones A, B, and C

Policy implications

The urban CEE in the middle reaches of the Yangtze River exhibits significant imbalance and spatial variations, with some cities showing great potential for improvement. Based on the findings of this study, the following strategic recommendations are proposed:

(1) Industrial structure, urbanization, population, technological innovation, economic development level, and energy consumption are crucial factors influencing the spatial spillover of CEE. These factors can be used to regulate urban CEE: Firstly, it is necessary to strengthen industrial upgrading and transformation and support the development of emerging industries. Secondly, in terms of urbanization, steady progress should be made in urban construction, promoting the intrinsic development and organic renewal of cities and establishing a low-carbon and green infrastructure network. Thirdly, optimize population structure, balancing growth with environmental harmony. Fourthly, enhancing technological innovation is key to improving CEE, particularly by increasing research and development efforts in low-carbon technologies, introducing and adopting advanced low-carbon technologies, and enhancing the core competitiveness in the low-carbon sector. Fifthly, develop green economies, with sustainable investments and nurturing low-carbon industries. Finally, reducing energy consumption in both sectoral and consumption domains is essential. This includes promoting clean energy and implementing measures to enhance energy efficiency in areas such as construction, transportation, industry, and agriculture. Additionally, encourage low-carbon transportation and lifestyles to establish green consumer preferences.

(2) Developing differentiated carbon reduction policies is crucial. There are variations among cities in terms of economic development level, resource endowment, technological innovation capacity, and ecological governance ability. Therefore, it is necessary to set corresponding emission reduction targets based on the actual circumstances (Wang and Li 2023). Based on the research results, we have divided the 42 cities into three zones: zones A, B, and C (Fig. 8).

Zone A: high carbon efficiency cities (e.g., Enshi, Yichang) with rich ecological assets—they should focus on carbon sequestration projects, limit resource-intensive industries, and harmonize development with environmental care.

Zone B: isolated high efficiency cities (e.g., Wuhan, Changsha) at the regional level—these cities can lead in technology, industry, and resource optimization and should collaborate with low-carbon peers.

Zone C: remaining cities with fluctuating carbon efficiency—they have potential for emission reduction and should reduce pollution and energy-intensive industries, promote green technology adoption, and enhance cooperation between academia, industry, and research for greener industries.

(3) Enhance regional collaborative governance mechanisms to narrow the gap in urban CEE. Due to the existence of regional spatial spillover effects, it is necessary not only to develop energy-saving and emission-reduction strategies at the city level but also to establish regional collaborative mechanisms from a regional perspective to generate synergistic emission-reduction effects (Liu et al. 2022b). It is recommended to leverage the Hubei carbon trading pilot to drive the development of the carbon market in the Yangtze River midstream urban cluster and improve market-led collaborative emission reduction mechanisms.

Innovations

We have discussed the spatial spillover effects and influencing factors of urban CEE, making some advancements compared to existing research. Firstly, existing studies on the influencing factors of CEE within the spatial context have mainly focused on research related to urbanization (Li et al. 2018), technological innovation (Zhang et al. 2023), and economic development (Liu et al. 2022a). Moreover, some articles have only explored the spatial effects of individual influencing factors. We have comprehensively considered important factors such as industrial structure, urbanization, population, vegetation coverage, technological innovation, economic development level, and energy consumption to establish a comprehensive index system. This helps reveal the complex and multidimensional spatial spillover mechanisms of CEE among cities. Secondly, unlike some previous studies that focused primarily on analyzing the temporal trends of CEE (Li et al. 2022), we created spatial distribution maps of CEE. This approach allowed us to better integrate both the temporal and spatial dimensions, providing a more comprehensive and visually intuitive representation of the evolving characteristics of CEE and its spatial clustering effects. Thirdly, the distribution of CEE in space is not random. Traditional econometric models do not account for spatial dependence and spillover effects between cities, which means they cannot capture the mutual influences among cities (Zeng et al. 2022). In light of this, following the calculation of urban CEE, we employed spatial analysis techniques to examine the spatial interdependence of CEE. Building upon the confirmation of the existence of spatial correlation, we constructed the SDM that incorporated a geographic adjacency matrix to evaluate spatial spillover effects. This approach helped us avoid potential regression errors resulting from neglecting spatial relationships.

Conclusion

This study is based on the calculation of CEE in the three provinces of the middle reaches of the Yangtze River in China. It evaluates the spatiotemporal characteristics of urban CEE from 2011 to 2019 and reveals the spatial spillover effect of CEE. Our findings can be summarized as follows:

(1) Based on the analysis of the spatiotemporal trends in urban CEE, we found that the overall CEE in the research area has been increasing over time. However, within each province, the cities exhibit varying patterns of CEE changes. Notably, there are significant differences in CEE among cities within Hubei and Hunan provinces, while the urban CEE in Jiangxi Province has shown a relatively stable evolution when compared to Hubei and Hunan. This indicates that CEE exhibits spatial heterogeneity with distinct characteristics based on provincial boundaries. Spatially, there is an observed pattern where eastern and northern regions tend to have lower CEE, while the western region exhibits higher CEE levels.

(2) Urban CEE exhibits a significant positive spatial autocorrelation with distinct Low-Low aggregation and Low–High aggregation characteristics. This indicates that within the research area, CEE demonstrates an uneven geographical distribution pattern. Low-Low aggregation primarily occurs in the peripheral regions, except for the northern part, while Low–High aggregation is observed in the central part of the study area, forming a circular clustering pattern around cities with high CEE.

(3) To further investigate the spatial effects and influencing mechanisms of urban CEE, we employed a spatial Durbin model and analyzed various factors. Through the decomposition of spatial effects, we found that industrial structure, urbanization, population, and energy consumption have negative effects on the CEE of both the focal city and neighboring cities, while technological innovation and economic development levels have the opposite effect. This suggests that the spatial

transmission mechanisms of urban CEE are complex and interrelated, and effective enhancement of CEE requires a coordinated effort involving these factors. Additionally, policy measures tailored to the heterogeneity should be considered for different types of cities.

This study also has several limitations. On the one hand, there are inherent uncertainties in the process of carbon emission calculation. Although the data used in this study are obtained from official statistics, there may be variations in data collection methods among different cities, even for the same indicators. On the other hand, the factors influencing CEE are diverse, and the selection of these factors can lead to variations in the research results. Furthermore, there are some areas for further exploration in future research. For example, the spatial effects of CEE are not limited to geographically adjacent cities. There may be specific spillover effects between cities based on industrial transfer or population mobility. Moreover, by expanding the research scale and scope, it would be possible to analyze the heterogeneity of spatial spillover effects in CEE in more depth.

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Data availability The datasets used or analyzed during the current study are available from the corresponding author on reasonable request.

Declarations

Ethical approval This article does not contain any studies with human participants or animals performed by any authors.

Consent to participate Not applicable.

Consent for publication Not applicable.

Competing interests The authors declare no competing interests.

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