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Evolution of carbon emission efficiency in the construction industry: Evidence from Guangdong-Fujian-Zhejiang coastal urban agglomeration in China

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Clarifying the changing characteristics and cyclical evolution of carbon emission efficiency in the construction industry is essential for formulating regional emission reduction policies and promoting cross-regional cooperation. This study focuses on the Guangdong-Fujian-Zhejiang coastal urban agglomeration as the research area and establishes an evaluation framework for the carbon emission efficiency of the construction industry from 2013 to 2022 based on the unexpected output Slack-based measure model. Data Envelopment Analysis is employed to examine the static distribution characteristics, while the Malmquist productivity index model is applied to assess the dynamic evolution patterns. Furthermore, synergistic carbon reduction strategies are proposed to support coordinated regional low-carbon development. Results show that: (1) The carbon emission efficiency of the construction industry in the Guangdong-Fujian-Zhejiang coastal urban agglomeration shows fluctuating growth in space and time, generally growing from west to east, with obvious spatial clustering, but there are large differences in the carbon emission efficiency of the construction industry between cities. (2) The total factor productivity of carbon emission in the construction industry shows positive growth. Among its decomposition indicators, changes in technical efficiency, changes in technological progress and pure technical efficiency promote the carbon emission efficiency of the construction industry, but changes in scale efficiency make a negligible contribution to the carbon emission efficiency of the construction industry. (3) Urban carbon emission efficiency shows obvious static-dynamic characteristics, with relatively high proportions of progressive mode and oscillatory mode, accounting for 37.50% and 31.25% respectively. This study provides a comprehensive static and dynamic analysis of the cyclical changes in the carbon emission efficiency of the construction industry, which provides a scientific basis for the formulation of differentiated energy-saving and emission reduction policies.

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Introduction

The global atmospheric concentration of carbon dioxide (CO₂) has continued to rise steadily, posing a serious threat to the sustainable development of human society and the stability of the ecological environment. This increase is associated with a range of adverse effects, including global warming, glacier retreat, ocean acidification, and more frequent extreme weather events (Li et al., 2024a; Lin & Li, 2024). A major driver of this trend is the persistent reliance on traditional fossil energy sources, which significantly contributes to carbon emissions and exacerbates climate change (Mishra et al., 2021; Sarkar et al., 2024). The 21st United Nations Climate Change Conference responded to this challenge by adopting the Paris Agreement's long-term objective, which seeks to restrict global temperature increase to 1.5°C (IPCC, 2018). China, being the world's second most prominent economy, has a significant role to play in achieving this objective (National Bureau of Statistics, 2023). Within China, the construction industry stands out as one of the three most energy-intensive sectors. It is characterized by high energy consumption, significant pollutant emissions, and relatively low energy efficiency, making it a major contributor to national carbon emissions and an essential focus for carbon reduction efforts (Chen et al., 2017; Huang et al., 2018; Li et al., 2025a).

According to the China Building Energy Consumption and Carbon Emission Research Report (2022) (Energy Consumption Statistics Committee of China Building Energy Conservation Association, 2023), the total CO₂ emissions from the construction industry reached 5.08 billion tons in 2020, accounting for approximately 50.9% of the country's total carbon emissions. On a global scale, China, along with India, the United States, and nearly 20 other countries, contributes to nearly three-quarters of total greenhouse gas (GHG) emissions (Mridha & Sarkar, 2025). Therefore, China has proposed to the world a two-stage "dual-carbon" goal of reducing emissions of CO₂ and other GHG emissions. Specifically, "carbon peaking" means that CO₂ emissions reach a maximum value in a given year and then begin to decline; "carbon neutral" means that CO₂ emissions and absorption reach a balance and net zero emissions are achieved (Han & Liu, 2024; Zhang et al., 2024a). It is of paramount importance for China to control CO₂ emissions and enhance carbon emission efficiency in the construction industry (CEECI) in order to achieve its "dual-carbon" targets (Du et al., 2019; Li et al., 2025b).

China is undergoing urbanization at an unprecedented speed, which has been described the largest human migration experiment in history (Bai et al., 2014; Lin et al., 2024a). Urban agglomerations play a crucial role in this process, acting as key platforms for driving national economic growth, promoting coordinated regional development, and enhancing international competitiveness and cooperation (Li et al., 2024b; Liao & Zhang, 2023). The Guangdong-Fujian-Zhejiang coastal urban agglomeration (GFZ-CUA) is strategically located within broader region encompassing the Yangtze River Delta (YRD), Pearl River Delta, Taiwan, and mainland China, in close proximity to Hong Kong and Macao. It serves as a vital corridor connecting southern and northern China, as well as bridging the eastern and western parts of the country. As a frontier platform, the GFZ-CUA plays an essential role in strengthening cross-strait exchanges and collaboration, contributing to the peaceful development of relations between mainland China and Taiwan. Due to the advantage of geographical location, open economy, and outward-looking development strategy, policy support, and other factors promoting the growth of demand for the construction industry, this study chooses the GFZ-CUA as the subject of research.

Under the guidance of the "dual-carbon" goal, the construction industry is facing urgent new requirements related to sustainable

development, smart technologies, green transformation, energy conservation, and emission reduction (Chang et al., 2018; Geng et al., 2012; Lin et al., 2024b; Luo et al., 2024). Carbon emission efficiency (CEE) promotes the synergistic development of economic growth and environmental protection by optimizing resource utilization, technological innovation, or management improvement in order to reduce CO₂ emissions per unit of output (Liu et al., 2018). Although studies at this stage have initially explored the spatial and temporal characteristics and influencing factors of CEE, they mainly focus on the inter-provincial or national level, ignoring the differences in economic and technological levels between cities, and still lack an analysis of the research on the evolutionary pattern of CEE in the urban construction industry.

In this study, GFZ-CAE was selected to evaluate CEECI. The region faces ecological and environmental challenges and has rich data resources. This study also analyzes the overall characteristics and evolution patterns of GFZ-CUA. The evolution patterns of CEECI dynamic indicators over time are explored in depth. At the same time, the study seeks to decompose city-level efficiency, identify the cycles of efficiency changes, and propose differentiated measures accordingly.

This study aims to make the following contributions: (1) Developing a comprehensive analytical framework that integrates static efficiency measurement, dynamic trend analysis, and typological pattern identification, enabling a multidimensional examination of the characteristics of CEECI and uncovering the underlying causes of inter-city efficiency disparities. (2) Introducing a new perspective for identifying low-carbon cities and examining the respective impacts of technological efficiency and scale effects on carbon emissions, offering important insights for promoting coordinated emission reduction and sustainable development in the regional construction sector. (3) Providing a strategic foundation for advancing carbon reduction and sustainable development goals in the regional construction industry, offering valuable guidance for long-term planning and the formulation of differentiated carbon neutrality policies in the GFZ-CUA. Furthermore, the proposed framework and findings have the potential to be applied to broader CEECI research and extended to other urban agglomerations.

The study is structured as follows. Section 2 reviews the literature on CEE and the development patterns of the construction industry. Section 3 presents the study area and methodology. The results are shown in Section 4. Section 5 provides a discussion of the findings, and Section 6 concludes.

Literature review

Currently, countries worldwide are prioritizing the reduction of carbon emissions. Improving CEE is universally recognized as one of the most effective means to accomplish social, economic, and environmental objectives (Wang et al., 2024; Yue & Yin, 2023; Zhang et al., 2019). CEE was originally defined as "carbon productivity," which is the ratio of GDP in a given period to carbon emissions in the same period (Kaya & Yokobori, 1993). Subsequently, CEE has been widely applied in the field of economics and interpreted as the combined economic and social value generated relative to carbon emissions from economic activities. It captures not only the dynamic relationship between carbon emissions and economic output but also the complex interaction between environmental impacts and economic returns. Single-factor carbon emission efficiency (SFCEE) focuses on assessing specific impacts of individual factors on carbon efficiency, such as carbon intensity, carbon productivity, and energy carbon intensity (González et al., 2015). In contrast, total

factor carbon emission efficiency (TFCEE) serves as a multi-dimensional evaluation metric, encompassing the comprehensive utilization efficiency of various input factors in the production process, thus providing a more comprehensive perspective for the assessment of CEE (Cheng et al., 2018).

In the analysis of a multi-input system, carbon emissions are defined as an unexpected output variable (Zaim & Taskin, 2000). In addition, efficiency measures have been enriched with Data Envelopment Analysis (DEA) and Stochastic Frontier Analysis (SFA). Since the DEA method was first applied to quantify CEE of the construction industry, modeling approaches have undergone continuous refinement. Notable advancements include the development of the three-stage DEA model (Li & Lin; 2016; Wang et al., 2011), the unexpected output Slack-based measure (SBM) model (Yang et al., 2018), the super-efficient SBM model (Wang et al., 2011), and the unexpected output super-efficient SBM model (Zhang et al., 2024b). More recently, the latest improvements to the SBM model have enabled a more scientific evaluation of CEE, thereby promoting the low-carbon development of the construction industry (Zhou et al., 2019).

The origins of the Malmquist index in DEA modeling can be traced back to Farrell's (1957) theory of performance evaluation and Malmquist's (1953) examination of production efficiency changes. Later, Caves et al. (1982a) combined the Malmquist index with a DEA model, introducing a method that enabled the evaluation and comparison of the performance of Decision-making Units (DMUs) and the identification of trends in efficiency alterations. The model has been used to measure efficiency and examine factors affecting the financial, agricultural, ecological and transportation industries, which are crucial for targeted management decisions and policy formulation (Banker et al., 1984; Baráth et al., 2024; Fare et al., 1994; Meng et al., 2023; Zhang et al., 2015). Additionally, this model has been extended to the construction sector, where it has been utilized to explore performance indicators of CO₂ emissions and to expand the measurement method of CO₂ emissions (Cheng et al., 2022).

Currently, the CEECI has been improving across most provinces in China, exhibiting a gradual decline from the higher levels observed in the eastern region to lower levels in the central and western regions (Zheng et al., 2019). Based on spatial and latitudinal regional differences, this modification is impacted by various factors, including building size, population density, urbanization rate, environmental regulations, and carbon trading policies (He & Song, 2022; Li et al., 2024c; Liu et al., 2018; Tian et al., 2014; Wang & Liu, 2024; Zhou et al., 2019). The spatial network of CEECI presents a "core-edge" pattern, consisting of a gradual breakdown of the hierarchical network structure (Ren & Li, 2024). Economically developed provinces tend to lead other provinces in improving CEE (Huo et al., 2022; Wang et al., 2025a). At the national level, several regions are encountering sluggish efficiency growth, and advancements in technology are driving greater improvements in CO₂ emission performance compared to enhancements in management (Cheng et al., 2022). In the YRD region, the carbon emissions of the construction industry (CECI) have shown a pattern of initial growth followed by fluctuating changes. An overall spatial pattern has emerging, featuring higher efficiency in the western areas and lower efficiency in the eastern areas, alongside clear signs of geographic concentration. These trends point to clear spatial spillover effects (Liu et al., 2023a; Zhang et al., 2022). Simultaneously, it has been found the CEE in this industry has improved and the disparities have decreased across cities (Du et al., 2022). Therefore, in order to advance CEECI, it is essential for cities to continue restructuring their energy consumption structure and enhancing their levels of technological development and modernization.

The study of efficiency evolution models provides an effective approach for analyzing dynamic processes and identifying cyclical changes. This methodology has been widely applied across various industries, including the economy, agriculture, tourism, manufacturing, and land use (Deng et al., 2023; Baráth et al., 2024; Joel, 2016; Foster et al., 2017; Lee, 2021; Zhang & Choi, 2013). For example, Jin et al. (2023) investigated the impact of the industrial integration on the evolutionary patterns of total factor productivity (TFP) in the forestry sector. Their analysis elucidates the theoretical relationship between integration and productivity evolution, providing important insights for the development regional forestry policies. The application of evolutionary models thus offers new research perspectives and practical strategies for forestry management. Similarly, Tian et al. (2024) introduced an evolutionary model to explore the spatial and temporal distribution, dynamic evolution, and patterns of carbon metabolism efficiency within the urban tripartite spatial system. This study contributes to the integration of regional factors and spatial optimization.

Much of the current research on CEECI has been conducted at the national or provincial level, with less attention paid to variations in emissions between cities. In particular, there is a lack of research on the GFZ-CUA, which has become another prominent urban agglomeration in China after the YRD, the Pearl River Delta and the Beijing-Tianjin-Hebei region. Significant differences exist among cities within the GFZ-CUA in terms of resource endowments, population size, technology level and other aspects. Therefore, previous studies have largely overlooked inter-city differences in scale efficiency and specific local conditions. Second, when analyzing efficiency, the emphasis is placed on the temporal and spatial distribution characteristics of overall efficiency, as well as on the investigation of spatial effects. However, there is a lack of comprehensive research on the decomposition of CEECI and the cyclical characteristics of various efficiency indices and their evolution over time. Finally, in-depth exploration of synergistic emission reduction effects at the regional level remains insufficient, limiting the practical implementation of differentiated policy measures across cities.

To remedy the above shortcomings, based on the input-output perspective, this study adopts the whole life-cycle approach to construct the CEECI assessment framework, introduces the non-expected output DEA model and the Malmquist index model. The main achievements of this research are as follows. First, this study analyzes the CEECI of GFZ-CUA in terms of technical efficiency and scale efficiency. Then, the research explores the static-dynamic characteristics of each city according to "efficiency scale-efficiency change" and defines the type of CEECI in each city. Finally, the research analyzes the cycle evolution of each city type during the period of 2013-2022 and classifies their respective evolution modes. This research framework can be extended to other CEECI in other regions worldwide, which will help to enhance the opportunities for CEECI and guide the regional building sector in coordinating emission reductions. Revealing the evolution patterns of the CEECI in each city provides an important reference for the differentiated formulation of policies and sharing of practical experience.

Study area and methodology

This study employed a combination of qualitative and quantitative methodologies to investigate the CEECI within the GFZ-CUA (Fig. 1). Firstly, a comprehensive evaluation framework was established by integrating the full life cycle approach with an input-output perspective to evaluate the CEECI (Amiri et al., 2021; Li et al., 2022b; Li et al., 2021). Secondly, the DEA model and Malmquist index model were employed to evaluate both the

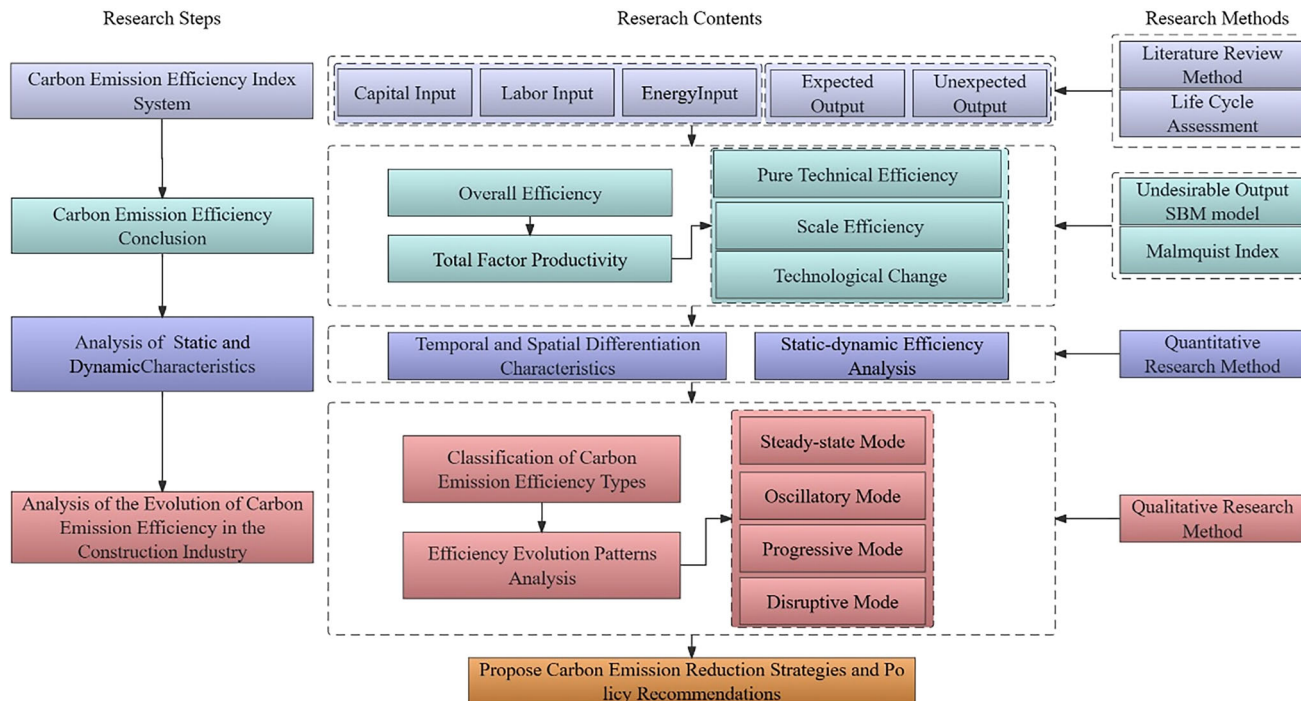


Fig. 1 The research framework.

static and dynamic aspects of CEE. Subsequently, the natural breaks method in ArcGIS was utilized to analyze the spatial and temporal variations in efficiency changes, as well as changes in efficiency decomposition. Lastly, based on “comprehensive efficiency” and “efficiency change,” a quadrangle classification method was applied to categorize cities into different CEE types. The evolution modes of each type were then identified according to their dynamic changes and evolution trajectories. Correspondingly, targeted strategies and policy recommendations were proposed for cities exhibiting different evolutionary modes. Furthermore, the research framework developed in this study offers strong potential for extension and application to other regions.

Study area. As of 2020, the West Coast Taiwan Strait Urban Agglomeration Development Plan has been officially approved. The “West Coast Taiwan Strait Urban Agglomeration” has been replaced by the term “GFZ-CUA” in the Outline of the Fourteenth Five-Year Plan for the National Economic and Social Development of the People’s Republic of China and the Vision for the Year 2035 as of March 12, 2021 (The State Council of China, 2021). According to the “Outline of Vision 2035,” the annual GDP by the end of 2021 amounted to 1,149,237 billion Yuan. The GFZ-CUA had a GDP of 6,654.91 billion Yuan, comprising roughly 5.79% of the national GDP. The total population of the country reached 1.41 billion people in late 2021. Meanwhile, the resident population of the urban agglomeration was 75.57 million people, comprising approximately 5.35% of the national population. Urban agglomeration has witnessed an upward trend in urbanization. As a result, the construction industry has had ample opportunities for market extension and technological advancement. However, the fast growth of the construction industry in the urban agglomeration has also led to challenges, including increased resource consumption and carbon emissions (Xu et al., 2024).

Since the updated GFZ-CUA Development Plan has not yet been formally released, this study refers to the original West

Coast Taiwan Strait Urban Agglomeration Development Plan and related policy documents. The study area is delineated into the following 16 cities: Shantou, Jieyang, Chaozhou, and Meizhou in Guangdong Province; Fuzhou, Quanzhou, Xiamen, Putian, Zhangzhou, Sanming, Nanping, Ningde, and Longyan in Fujian Province; and Wenzhou, Lishui, and Quzhou in Zhejiang Province (Fig. 2).

Methods and models

Establishment of a CEE indicator system for construction industry. By analyzing the previous literature on CEECI accounting, it is found that the most important input factors are generally capital input, labor input, and energy input (Caves et al., 1982b; Deng et al., 2023; Dong et al., 2023; Li et al., 2022c; Li et al., 2023a; Pai & Elzarka, 2021; Zhang et al., 2019). The mechanism through which CO₂ emissions are generated during the economic activities of the construction industry is shown in Fig. 3.

TFCEE is defined as the maximum economic output achieved by the construction industry with the minimum carbon emission output through the production process of gradually increasing inputs and outputs (Cheng et al., 2018; Dong et al., 2022; Jiang & Li, 2022; Wei et al., 2019). This study summarizes the CEECI evaluation indicators recently studied (Table 1).

Considering both the indicators selected by the scholars mentioned earlier and the availability of model and data, the study establishes the following evaluation criteria for CEE. The input indicators are categorized into three main types. Firstly, the capital input is represented by the fixed asset investment in the construction industry. Secondly, the labor input is measured by the average number of employees in the construction industry at the end of each year. Lastly, the resource input includes factors such as energy consumption and the utilization of machinery and equipment. Among the output indicators, the gross output of the construction sector is selected as the desirable output, while CO₂ emissions from the construction industry are considered the undesirable output, as shown in Table 2.

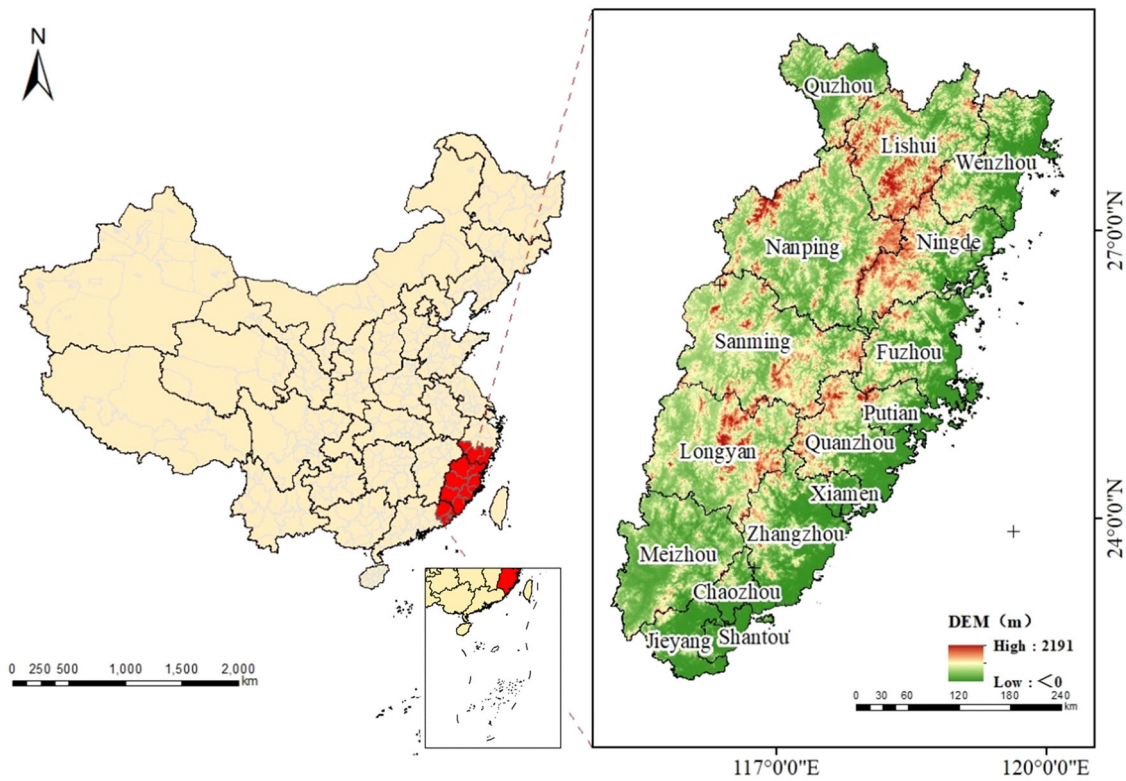


Fig. 2 Geographic location of the GFZ-CPA.

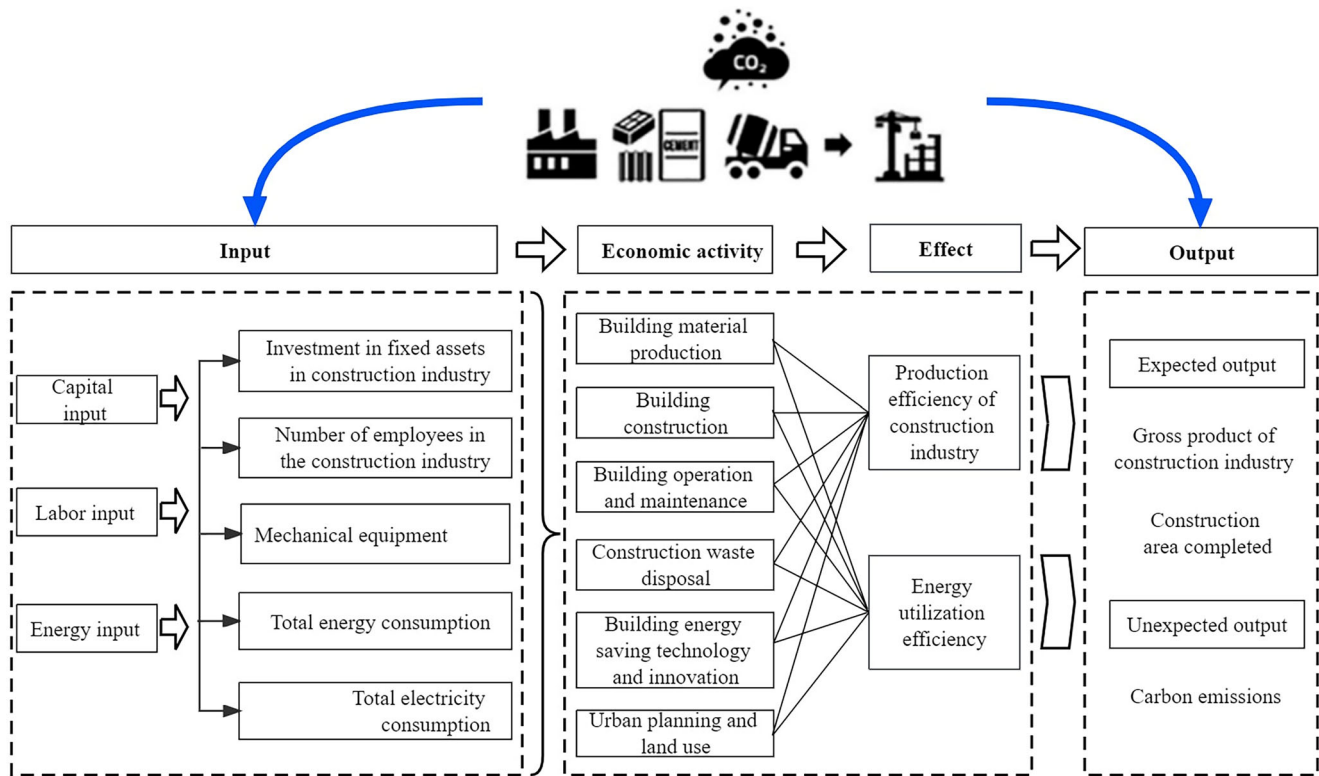


Fig. 3 Assessment framework of CEECI.

The data for each indicator are sourced from multiple references, including the China Urban Statistical Yearbook, the China Energy Statistical Yearbook, statistical yearbooks from provinces and cities, EPS and RESSET databases, statistical bulletins, and urban panel data. In cases where data were absent,

the average weighted data from adjacent years is substituted to complete the overall data set.

Unexpected output SBM model. The DEA method and its initial model were introduced by Charnes et al. (1978). The approach

Table 1 Evaluation indicator system.

Research methodology	Input variable		Output variable		References
	First-Level indicator	Second-level indicator	Expected output	Unexpected output	
Generalized DEA	Capital input	Enterprise-owned construction machinery	Economic output	-	(Li et al., 2023b; Lu et al., 2022; Sala-Garrido et al., 2023; Zaim & Taskin, 2000)
	Labor input	Average number of employees	Construction area		
	Machinery and equipment	Average value of total power of machinery and equipment			
	Construction CO ₂ emissions	CO ₂ emissions from energy consumption			
SBM	Capital input	Construction business assets	Economic efficiency	Negative environmental effect	(Wang et al., 2021; Yang et al., 2025; Zhou et al., 2006)
	Labor input	Number of employees in construction enterprises			
Ultra-efficient SBM	Energy input	Energy consumption	Gross product	CO ₂ emission factor	(Wang et al., 2025b; Yue & Yin, 2023; Zhang et al., 2017)
	Capital input	Investment in fixed assets	Floor space		
Labor input	Depletion of resources	Number of employees in construction enterprises			
	Capital input	-			
Unexpected output SBM	Energy input	End-use energy consumption	Gross product	CO ₂ emissions	(Cheng et al., 2022; Song et al., 2019; Zhou et al., 2010)
	Capital input	Net value of owned construction machinery and equipment at year-end			
	Labor input	Number of people employed			
	Machinery and equipment	Total year-end power of owned construction machinery and equipment			
Unexpected output super-efficiency SBM	Capital investment	Investment in fixed assets	Gross product	CO ₂ emissions	(Shu et al., 2024; Yu et al., 2019; Zhang et al., 2024b)
	Labor force	Number of persons	Floor space		
Unexpected output super-efficiency SBM	Renewable energy	Consumption of fossils, energy and building materials			
	Capital investment	Investment in fixed assets	Gross product	CO ₂ emissions	(Shi & Wang 2024; Zhang et al., 2024c; Zhou et al., 2019)
Unexpected output super-efficiency SBM	Labor input	Number of persons			
	Machinery and equipment	Total power of construction machinery and equipment			

The above indicators refer to the construction industry.

Table 2 Indicator system of CEECI.

First-level indicator	Second-level indicator	Definition of indicator	Unit
Input variable	Capital input	Fixed assets in the construction industry	10 ⁶ Yuan
	Labor input	Average number of employees in the construction industry at the end of the year	10 ⁴ persons
	Resource input	Machinery and equipment	kWh
		Energy consumption	tons
Output variable	Expected output	Gross product of construction industry	10 ⁶ Yuan
	Expected output	Negative environmental effects in the construction industry	10 ⁴ tons

determines the production efficiency of various DMUs with multiple input and output factors of similar nature. During the production process of construction projects, labor, capital, and energy inputs generate not only construction products but also create unwarranted by-products like the emission of CO₂. When using the DEA model to assess production activity efficiency with unexpected output, limitations arise as the model must rely on “radial” or “angle” measurements (Banker et al., 1984; Charnes et al., 1978). The SBM model, proposed by Tone and based on non-radial and non-angle measurements, resolves productivity slack and inefficiency issues in scenarios with unexpected output (Tone, 2001).

This study presents an unexpected output SBM model for evaluating CEE. Suppose there are n production activities of decision units, each of which has three vectors of inputs, expected outputs, and unexpected outputs and can be expressed as respectively: $x \in R^m$, and $y^g \in R^{s_1}$ and $y^b \in R^{s_2}$ and the matrices X, Y^g and Y^b can be defined as $X = [x_1, x_2, \dots, x_n] \in R^{m \times n}, Y^g = [y_1^g, y_2^g, \dots, y_n^g] \in R^{s_1 \times n}$, and $Y^b = [y_1^b, y_2^b, \dots, y_n^b] \in R^{s_2 \times n}$, where $X > 0, Y^g > 0, Y^b > 0$. Then the set of production activity possibilities can be described as:

$$P = (x, y^g, y^b) | x \geq \lambda X, y^g \leq \lambda Y^g, y^b \geq \lambda Y^b, \lambda \geq 0 \tag{1}$$

where λ is a nonnegative intensity vector, indicating that the above definition corresponds to the condition of constant returns to scale.

Based on the set of production activity possibilities, the unexpected output SBM model according to Tone’s proposal can be expressed as follows:

$$\rho^* = \min \frac{1 - \frac{1}{m} \sum_{i=1}^m \frac{s_i^-}{x_{i0}}}{1 + \frac{1}{s_1 + s_2} \left(\sum_{r=1}^{s_1} \frac{s_r^g}{y_{r0}^g} + \sum_{r=1}^{s_2} \frac{s_r^b}{y_{r0}^b} \right)} \tag{2}$$

$$st. \begin{cases} x_0 = \lambda X + s^- \\ y_0^g = \lambda Y^g - s^g \\ y_0^b = \lambda Y^b + s^b \\ s^- \geq 0, s^g \geq 0, s^b \geq 0, \lambda \geq 0 \end{cases} \tag{3}$$

where ρ^* is the CEECI, and $s = (s^-, s^g, s^b)$ denotes the slack variables of inputs, expected outputs, and unexpected outputs, respectively. With respect to s_i^-, s^g , and s^b are strictly decreasing, and $0 \leq \rho^* \leq 1$. For a particular DMU, it is efficient if and only if $\rho^* = 1$, that is, $s_i^- = 0, s^g = 0$, and $s^b = 0$. If $\rho^* < 1$, it signifies an efficiency gap between DMUs and other units at a specific scale, and a necessity for bettering resource utilization currently in place.

Malmquist model. The Malmquist model combines the technical change (TC) index and the efficiency change (EC) index to evaluate the comprehensive change of production efficiency of each DMU in different periods (Lovell & Wu, 1999). Therefore, this study uses the Malmquist index with unexpected output to measure the dynamic change characteristics of CEECI in each city. The Malmquist index is defined as:

$$MTFP = MEC \times MTC = MPEC \times MSEC \times MTC \tag{4}$$

where TFP is the total factor productivity, which characterizes the degree of change in the CEECI from 2013 to 2022 for each decision unit. If $MTFP > 1$, the TFP of CEECI rises; if $MTFP < 1$, the TFP of CEECI decreases; if $MTFP = 1$, then it has no change. The formula is further decomposed into EC and TC, where EC characterizes the approximation of the production efficiency of the DMUs to the production frontier level, and TC represents the movement of the DMUs to the production frontier level. And

then EC is further decomposed into Pure Efficiency Change (PEC) and Scale Efficiency Change (SEC).

Results

Spatial and temporal pattern of CEECI in the GFZ-CUA

Temporal characteristics of CEE. Based on the time evolution analysis presented in Table 3, the carbon emission efficiency (C) of the construction industry in each city within the study area exhibited a consistent upward trend from 2013 to 2022. The growth rate notably accelerated after 2020, reflecting the impact of the emission reduction policies implemented in the construction industry. However, significant disparities in CEECI exist across different cities. Overall, the industry’s average CEE increased from 0.650 in 2014 to 0.817 in 2022. Cities such as Shantou, Chaozhou, and Quanzhou reported relatively high average CEECI values, with Shantou maintaining an efficiency score of 1, indicating that the industry in these cities operates on the production frontier, effectively controlling carbon emissions while promoting economic development. In contrast, seven cities fell below the average CEECI level, with Longyan, Zhangzhou, and Nanping occupying the lowest positions. The efficiency values for these cities remain consistently low with minimal changes, suggestive of a delayed development of CEECI. This aspect is largely due to a lack of necessary norms and policy support, leading to energy waste and inefficient equipment utilization.

In terms of efficiency decomposition analysis from 2013 to 2022, pure technical efficiency (V) demonstrated a fluctuating growth trend, increasing by 1.11 times, with an average annual growth rate of 2.2%. Among the cities, Xiamen, Quanzhou, and Quzhou achieved mean pure technical efficiency values greater than 1. In contrast, Shantou, Fuzhou, and Wenzhou have a mean value of pure technical efficiency equal to 1, signifying that the construction industry in these cities is less efficient in both resource utilization and CEE. Conversely, Zhangzhou, Nanping and Ningde exhibited relatively low pure technical efficiency, suggesting issues related to resource wastage and low operational efficiency.

Regarding scale efficiency (S), the overall trend was also fluctuating, with an average annual growth rate of 3.1%. Notably, Chaozhou, Fuzhou, Sanming and Wenzhou demonstrated higher levels of scale efficiency in the construction industry, whereas Nanping, Ningde, Jieyang relatively exhibited low scale efficiency in the construction industry. The findings suggest that the construction industry in certain cities has experienced significant growth. Thus, it is crucial to enhance energy and resource utilization efficiency while promoting the full implementation of carbon emission reduction technology to attain the benefits of large-scale operation within the urban construction industry.

By analyzing the returns to scale (R-S), the number of cities with increasing returns to scale first decreases and then increases. The number of cities with diminishing returns to scale changes in the opposite direction. However, the number of cities with constant returns to scale increases. Specifically, the construction industry’s return to scale is increasing in Chaozhou, Fuzhou and Sanming, whereas cities such as Zhangzhou, Nanping, and Wenzhou exhibited decreasing returns to scale. Therefore, it is reasonable to decrease the amount of material resources used for energy input and resource production in the construction industry of the mentioned cities to enhance the return to scale.

Spatial characteristics of CEE. Based on ArcGIS visualization software, this study explores the spatial distribution characteristics of CEE and decomposition efficiency of the construction industry in the GFZ-CUA. The natural breakpoint classification

Table 3 CEE and decomposition efficiency of construction industry.

Vintage	2014			2016			2018			2020			2022			
	C	V	S	R-S	C	V	S	R-S	C	V	S	R-S	C	V	S	R-S
Shantou	1.000	1.000	1.000	drs	1.000	1.000	1.000	drs	1.000	1.000	1.000	drs	1.000	1.000	1.000	irs
Chaozhou	1.000	1.000	1.000	irs	0.836	1.000	0.954	irs	0.818	1.000	0.932	irs	1.000	1.000	0.982	irs
Jieyang	1.000	1.000	1.000	irs	0.888	1.000	1.000	drs	0.824	1.000	1.013	irs	0.712	1.000	0.934	irs
Meizhou	1.000	1.000	1.000	irs	0.785	1.000	1.000	drs	0.690	1.000	1.000	drs	0.759	1.000	1.000	irs
Fuzhou	0.691	1.000	1.424	irs	0.614	1.000	1.000	drs	0.733	1.000	1.000	irs	0.798	1.000	1.000	irs
Xiamen	0.582	0.812	1.082	drs	0.629	1.000	1.000	drs	0.629	1.000	1.000	drs	0.780	1.154	0.870	irs
Quanzhou	0.644	1.000	1.000	irs	0.867	1.000	1.000	irs	0.919	1.000	1.000	irs	1.000	1.000	1.000	irs
Putian	0.343	0.781	1.017	drs	0.619	1.066	0.982	drs	0.431	1.066	1.067	irs	0.620	1.086	1.087	irs
Zhangzhou	0.404	0.818	0.636	irs	0.408	1.133	0.927	drs	0.383	0.971	1.151	irs	0.451	1.080	1.161	irs
Nanping	0.359	0.803	0.755	irs	0.558	1.185	1.284	drs	0.521	1.000	1.289	irs	0.685	1.000	1.000	irs
Wenzhou	0.418	0.938	0.789	irs	0.530	1.058	0.990	drs	0.599	0.925	0.867	irs	0.475	1.108	1.000	irs
Longyan	0.411	1.006	0.981	irs	0.467	1.107	0.998	irs	0.540	0.854	1.017	irs	0.602	0.998	1.016	irs
Wenzhou	0.679	1.000	1.000	irs	0.782	1.036	1.001	irs	0.403	0.867	0.993	irs	0.456	1.048	1.183	irs
Lishui	0.516	1.000	1.000	irs	0.580	1.000	1.000	drs	0.581	1.000	1.000	drs	0.741	1.000	1.264	irs
Quzhou	1.000	1.000	1.000	irs	0.874	1.000	1.000	drs	0.549	0.872	0.988	irs	0.590	1.000	1.000	irs
Mean	0.650	0.966	1.028	irs	0.676	1.013	1.006	irs	0.687	0.979	1.001	irs	0.704	1.002	1.015	irs

C denotes construction carbon efficiency; V the pure technical efficiency; S the scale efficiency; R-S the returns to scale; irs the increasing returns to scale; drs the decreasing returns to scale and “-” the constant returns to scale.

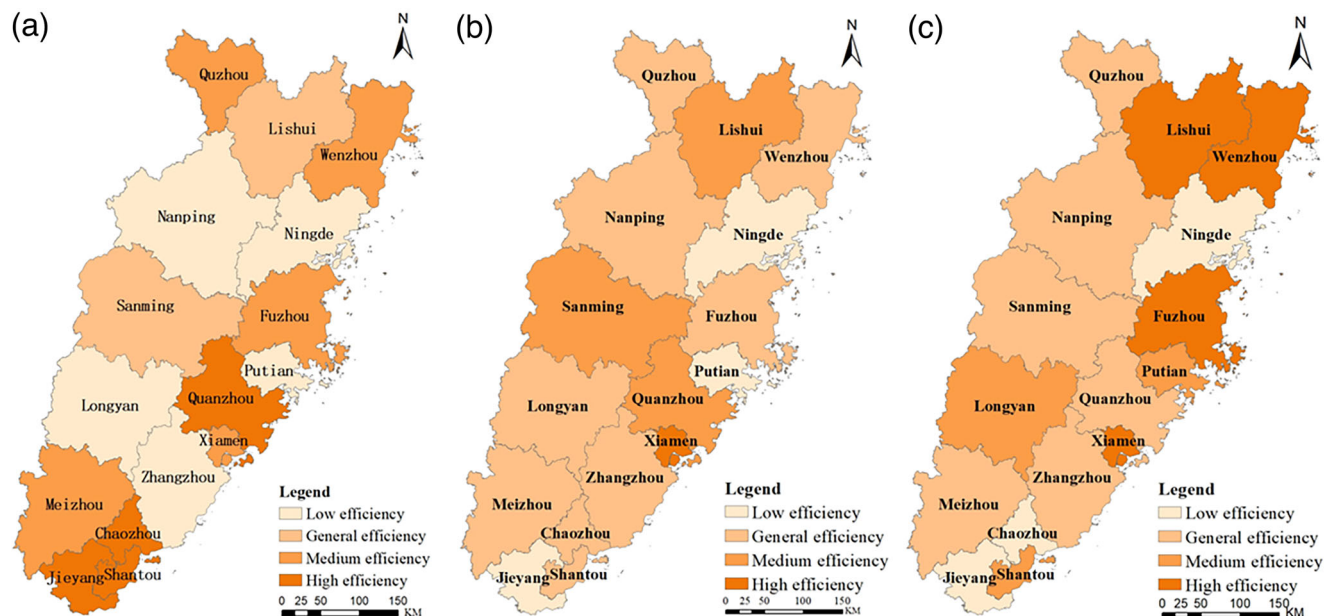


Fig. 4 Spatial distribution of CEE and decomposition efficiency. **a** CEE level. **b** Pure technical efficiency level. **c** Scale efficiency level.

method (Jenks) is used to divide the mean values of each CEE index into four categories: high efficiency, medium efficiency, general efficiency, and low efficiency (Fig. 4).

From 2013 to 2022, significant spatial differences in CEE and decomposition efficiency were observed within the study area, displaying an increasing trend from west to east along with obvious spatial aggregation. High-efficiency cities are predominantly concentrated in provincial capitals and coastal cities, including Quanzhou, Xiamen, Wenzhou and Chaozhou. The above cities from higher levels of resource endowment and urbanization. In contrast, cities with low efficiency, such as Nanping and Longyan, are primarily located in inland border areas. These cities are characterized by lower degree of urbanization, extensive development patterns in the construction industry, and a disharmonious ratio of resource input and output, which results in low CEECI.

In general, the proportion of cities with CEE, pure technical efficiency, and scale efficiency of the construction industry at or below the level of ordinary efficiency in urban agglomerations is 43.75%, 68.75%, and 56.25%, respectively. This indicates that the overall level of CEECI in the GFZ-CUA is low. Influenced by the unique geographical location of urban agglomerations and the stable and innovative economic base of each city, population growth leads to the acceleration of the urbanization process. A large amount of energy consumption and resource abuse in the construction industry has caused unexpected negative environmental impacts, contributing to the overall low levels of CEE observed in the region. To promote coordinated emission reduction of the construction industry in different cities requires the joint efforts of the government, enterprises, and the public in the process of resource utilization policy guidance. Specific measures and policies should be formulated according to the energy structure, climate conditions, and resource characteristics of different regions.

Dynamic analysis of carbon emissions efficiency change. As shown in Table 4, the average value of TFP in the construction industry in the GFZ-CUA is greater than 1, indicating an overall upward trend in productivity change. The average values of EC, TC, PEC, and SEC in the decomposition indicators are all greater

than 1, indicating that each of these factors contributes to improvements in CEECI. Among them, however, the contribution of SEC is relatively smaller compared to the other indicators.

As shown in Fig. 5, between 2013 and 2022, over 60% of the cities in the study area showed an upward trend in TFP. Cities with the highest values are primarily Meizhou, Xiamen, Zhangzhou, and Lishui, while the lowest values are mainly observed in Quzhou, Sanming, and Shantou. These variations can be attributed to differences in the economic and industrial structure of each city. Regarding TC, 62.50% of the cities demonstrated improvements. Among them, Chaozhou, Wenzhou, and Jieyang reported higher TC, while Shantou, Quzhou, and Sanming have lower TC. This suggests that the latter cities need to focus on strengthening technological upgrading in their energy development and utilization processes.

The PEC of CEECI varies significantly across cities. Only 18.75% of the cities show a downward trend in PEC, including Jieyang, Zhangzhou, and Quzhou. This highlights that these cities need to upgrade and transform the traditional, resource-intensive modes of production and resource utilization within the construction industry.

In the process of improving the CEECI, only 37.50% of the cities have achieved scale efficiency improvement. Sanming, Longyan, and Ningde exhibited higher SEC, while Fuzhou, Putian, and Quzhou showed lower performance. Cities with higher SEC tend to emphasize the development and deployment of energy technologies, thereby enhancing industrial agglomeration and accelerating the formation of scale effects in the construction industry.

Evolution characteristics of CEECI in the GFZ-CUA

Typological characterization. To gain a comprehensive understanding of changes in CEECI in the GFZ-CUA, this study combined the comprehensive efficiency value (C) derived from the DEA model with the TFP obtained from the MI to construct a quadrant graph illustrating “efficiency size-efficiency change.” The average overall efficiency from 2013 to 2022 is 0.70, which serves as the benchmark for the horizontal axis (“efficiency range”). A MI value greater than 1 suggests an enhancement of CEECI, while a value less than 1 implies a decline in efficiency. As such, the threshold value for “efficiency change” is established at 1

Table 4 Mean Malmquist index of CEECI, 2013–2022.

Time period	Total factor productivity (TFP)	Technical efficiency change (EC)	Technological progress Changes (TC)	Pure technical efficiency change (PEC)	Scale efficiency change (SEC)
2013–2022	1.052	1.019	1.033	1.014	1.005

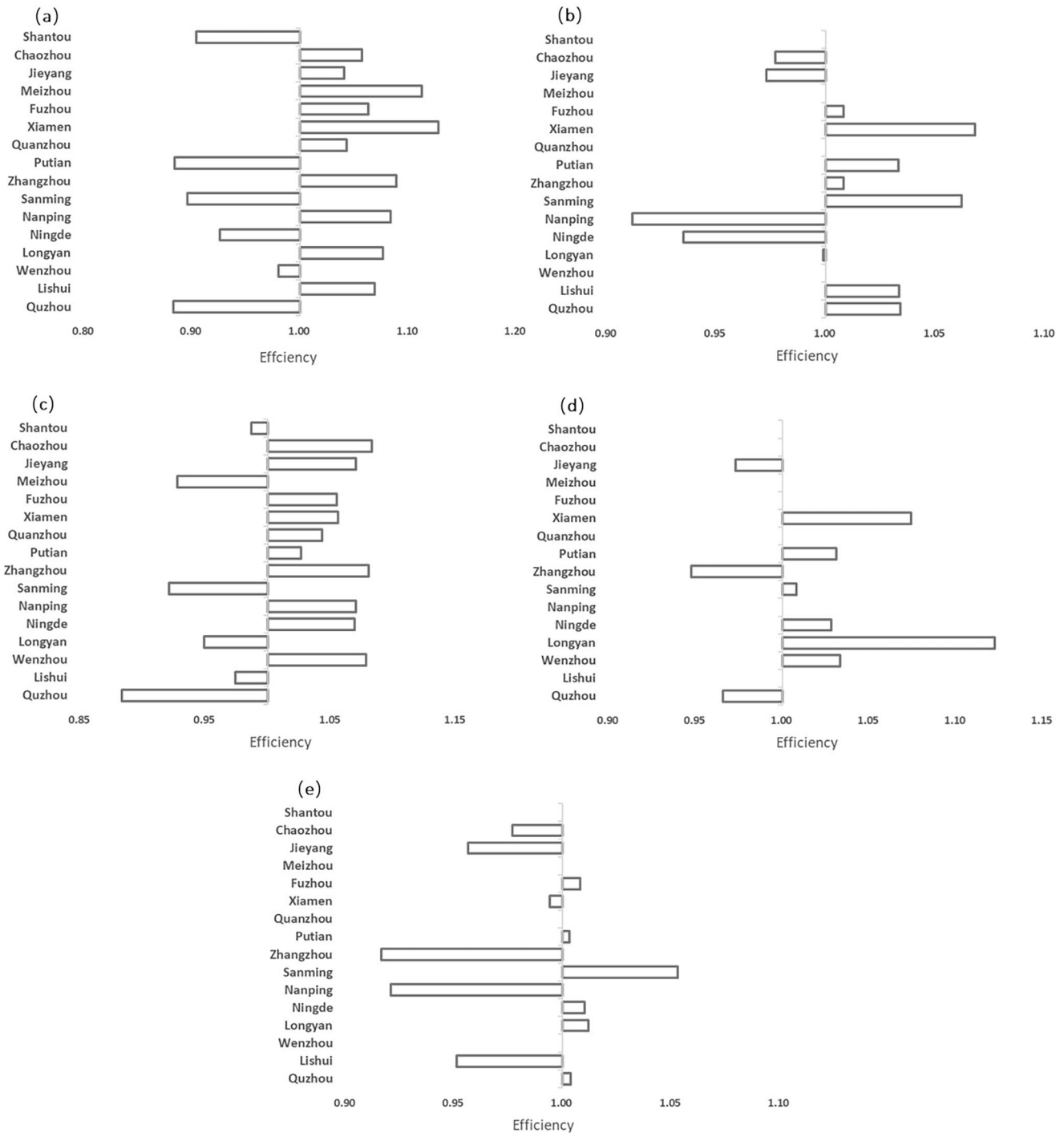


Fig. 5 Mean Malmquist index and decomposition of CEE. a TFP. b EC. c PC. d PEC. e SEC.

on the vertical axis. Therefore, the CEECI is divided into four different types, namely type I, type II, type III, and type IV (Fig. 6). Additionally, ArcGIS software was utilized to visually represent the CEECI in the region, with a focus on its unique features each year (Fig. 7).

Type I, the high-efficiency type: the CEECI is high, and TFP is consistently growing. The carbon emission system of the construction industry in cities of this type is efficient. For example, the corresponding coordinates of Xiamen and Meizhou are (0.750, 1.128) and (0.830, 1.113), respectively. The city

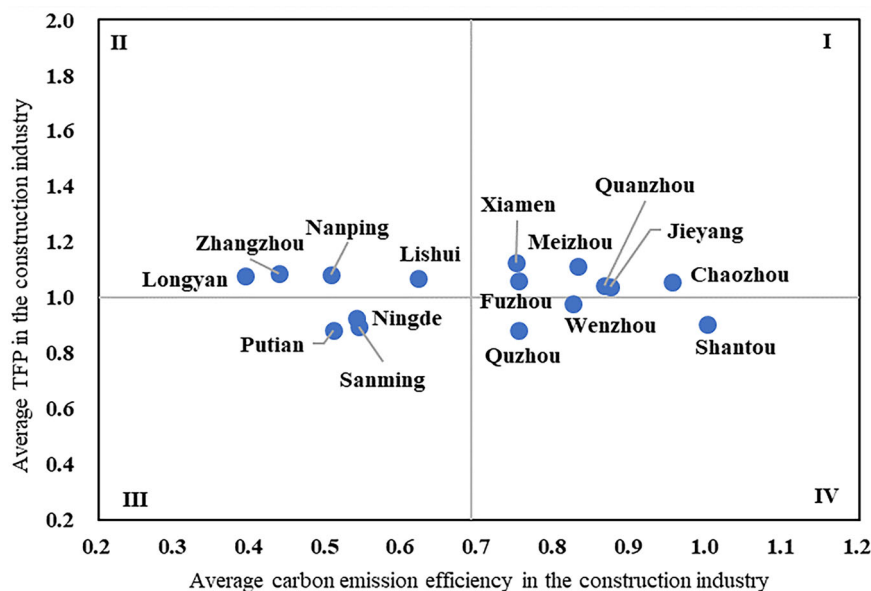


Fig. 6 Classification of types of CEECI.

exhibits considerable proficiency in comprehensive carbon emissions, and there is an upward trend in its TFP. Given the available inputs, the city’s CEEI is aligned with its production frontier, while its CEE continues to grow steadily.

Type II, the improved type: the CEECI is low, but TFP continues to grow. For instance, the corresponding coordinates of Longyan and Zhangzhou are (0.393, 1.077) and (0.438, 1.089), respectively. Although the CEECI isn’t high, the TFP has significantly increased. The development foundation of the construction industry in this type of city is relatively weak, but in the past period, the resource utilization and the excellent industrial structure have stimulated the potential of carbon emission reduction in the construction industry, and the TFP has been greatly improved.

Type III, the low-efficiency type: the CEECI is low and decreasing TFP. For example, the corresponding coordinates of Putian and Sanming are (0.508, 0.884) and (0.543, 0.896), respectively, indicating that the CEECI in these cities lags and the TFP is declining. The urban construction industry encounters issues like resource inefficiency, inadequate equipment utilization, limited energy diversification, inadequate building energy-saving design and emission reduction technology application, and subpar energy utilization efficiency.

Type IV, the declining-efficiency type: the urban construction industry has a higher CEE, but the TFP declines. For example, the corresponding coordinates of Shantou and Quzhou are (1.000, 0.904) and (0.752, 0.883), respectively. This category of cities has reached a comparatively high level of CEEI but has experienced little change in efficiency. Due to the low energy and technology utilization rates in the urban construction industry, there is a lack of coordinated resource and material input, resulting in a relatively low TFP of carbon emissions.

Evolutionary model. By examining the CEECI in the GFZ-CUA and its temporal changes, it is observed that the dynamic evolution of carbon emission types across urban construction industry exhibits diverse patterns over the past decade.

Therefore, based on references to previous studies, this study combines the CEE changes of the construction industry in 16 cities in the GFZ-CUA (Table 5). The evolution patterns of

CEECI can be classified into four distinct types: steady-state mode, oscillatory mode, progressive mode, and disruptive mode. The typical city evolution patterns are plotted as shown in Fig. 8.

- (1) **Steady-state mode:** The trend for change in the comprehensive efficiency of carbon emission and TFP within the urban construction industry is predominantly stable, with corresponding coordinate points consistently located within a fixed quadrant. Among the 16 cities analyzed, only Nanping is classified as stable, remaining in type II, which means it has low carbon emission comprehensive efficiency but significant efficiency variation. Nanping’s construction industry has not effectively implemented stable and efficient carbon emission reduction policies, resulting in its CEE remaining at a low level. There is a need to strengthen the implementation of emission reduction policies and achieve technological breakthroughs to reduce emissions and move beyond its current type II stable state.
- (2) **Oscillatory mode:** The direction changes of comprehensive efficiency of carbon emissions and TFP of urban construction industry are repeated, and their corresponding coordinate points move reciprocally in adjacent quadrants. The number of cities with a reciprocal evolution model in the region is relatively high, accounting for 31.25%, including Jieyang, Meizhou, Putian, and Longyan. These cities mostly demonstrate oscillatory evolution between type IV and type I, type II and type I, and type III and type II. This city model is susceptible to macroeconomic changes, policy modifications, or technological advancements.
- (3) **Progressive mode:** The trend in the comprehensive efficiency of carbon emissions and TFP of the urban construction industry follows a regular pattern with corresponding coordinate points slowly moving to adjacent quadrants. The number of cities with a reciprocal evolution model in the region is relatively high, accounting for 37.50%, including Jieyang, Meizhou, Putian, and Longyan. The energy supply and resource allocation are well-balanced, and there is considerable potential for the development of energy conservation and emission reduction.

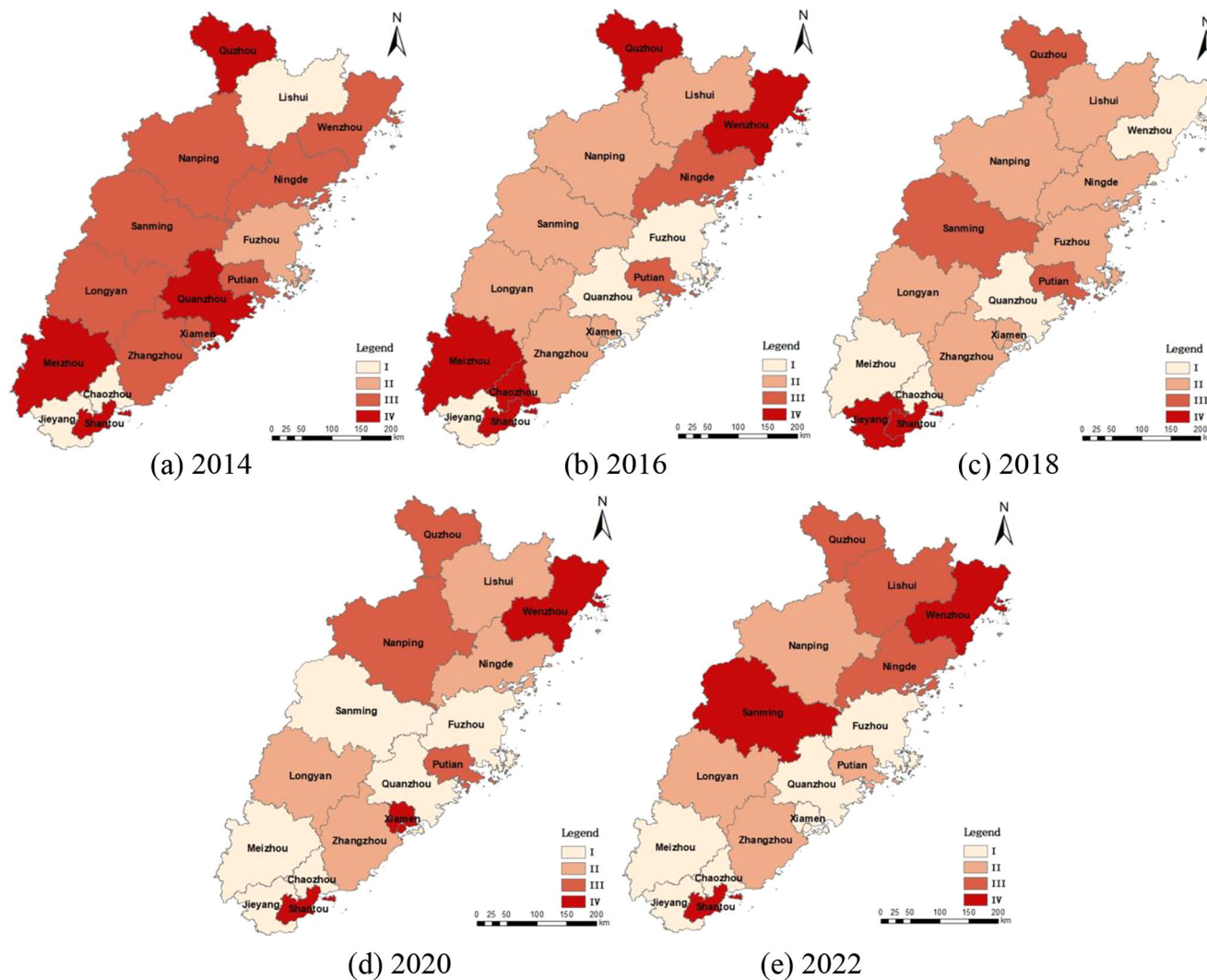


Fig. 7 Types of CEECI in the GFZ-CPA, 2014-2022.

Table 5 Evolutionary pattern of CEECI.

City	Type					Pattern
	2014	2016	2018	2020	2022	
Shantou	I	I	I	I	IV	Progressive mode
Chaozhou	IV	IV	IV	IV	I	Progressive mode
Jieyang	I	IV	I	I	I	Oscillatory mode
Meizhou	I	I	II	I	I	Oscillatory mode
Fuzhou	I	II	I	IV	IV	Disruptive mode
Xiamen	III	III	IV	I	I	Disruptive mode
Quanzhou	II	IV	I	IV	I	Disruptive mode
Putian	II	III	II	III	II	Oscillatory mode
Zhangzhou	III	II	II	II	II	Progressive mode
Sanming	II	II	II	III	IV	Disruptive mode
Nanping	II	II	II	II	II	Steady-state mode
Ningde	II	II	II	II	III	Progressive mode
Longyan	II	II	III	II	II	Oscillatory mode
Wenzhou	II	IV	IV	IV	IV	Progressive mode
Lishui	III	III	III	III	II	Progressive mode
Quzhou	IV	IV	III	III	I	Disruptive mode

- (4) Disruptive mode: the comprehensive CEECI is unstable, the change trend of TFP is irregular, and its corresponding coordinate points move irregularly within 3 or 4 quadrants. Among them, cities like Fuzhou, Xiamen, Sanming, and

Quzhou show significant variations in CEE within this model, but it has a common feature of unstable CEE. This sudden change is usually caused by major policy adjustments, technological breakthroughs, and changes in industrial structure.

Discussion

From 2013 to 2022, the comprehensive efficiency of intercity carbon emissions in GFZ-CPA showed an increasing trend from west to east, characterized by uneven spatial distribution and obvious spatial aggregation. This result confirms the research conducted by Du et al. (2022) on the spatial differentiation of carbon emissions from regional construction industry.

From the perspective of decomposition efficiency characteristics, the mean values of TFP, EC, TC, PEC, and SEC are all greater than 1, indicating an upward trend in TFP in the study area. However, SEC’s contribution to CEECI is not significant enough. Therefore, it is necessary to strengthen the relationship between carbon emissions and production scale (Chen & Zheng, 2023). Cities with the trend of optimization and improvement of TFP accounted for more than 60%, cities with TC in the process of CEE improvement accounted for 62.50%, areas with the trend of decline in PEC accounted for only 18.75%, and cities with SEC accounted for only 37.50%. The reasons for this difference are the city’s economic level, location conditions, policies, and

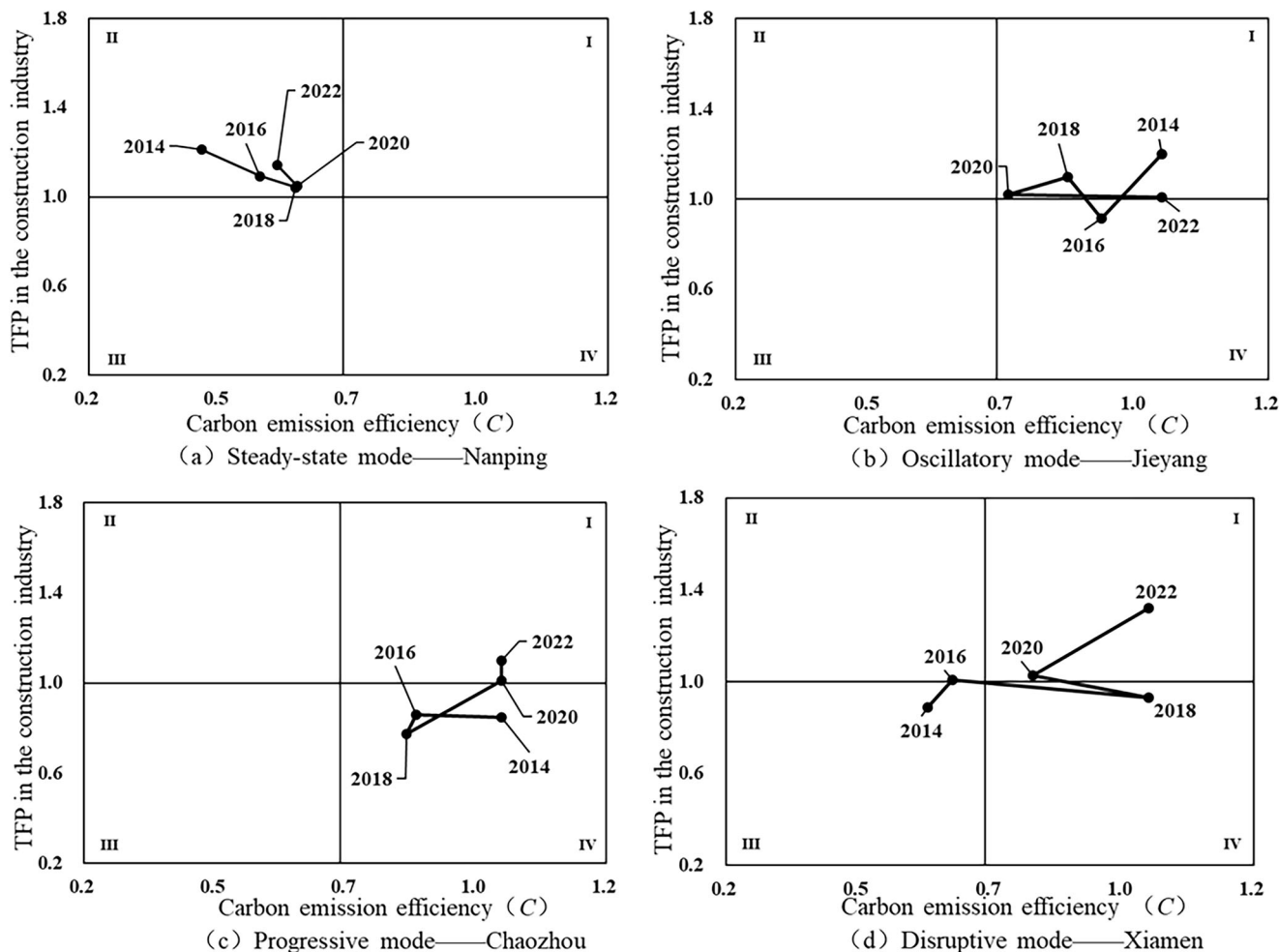


Fig. 8 Types of carbon efficiency evolution models.

regulations, building structure planning and type selection (Li et al., 2022a; Wang et al., 2022), energy utilization and management level, technology innovation and application, etc. (Yuan et al., 2023; Zhou et al., 2019).

Furthermore, intercity variations in efficiency and decomposition efficiency may also be affected by the performance of neighborhood cities (Du et al., 2022). When a city is adjacent to a high-performing region, its carbon emission performance tends to cluster and improve overall (Wang et al., 2021; Zhang & Jia, 2019).

The categorization of CEEI based on comprehensive efficiency and TFP offers several benefits. These benefits include identification of low-carbon cities that lead the way, provision of targeted policy guidance, and promotion of experience exchange and collaboration among urban areas (Dong et al., 2022; Hou et al., 2012). Such categorization supports the construction industry in progressing towards low-carbon development (Huang et al., 2022; Liu et al., 2023b). After classifying the CEE types of the construction industry in GFZ-CUA, it was determined that Xiamen and Meizhou have higher CEE. Zhangzhou and Longyan have potential for improvement, while Putian and Sanming have lower efficiency. The efficiency of Shantou and Quzhou continues to deteriorate. The CEEI varies between cities due to factors such as building energy efficiency, the stage of construction industry development, building materials and technology, and building scale and density (Wang et al., 2020). As a result, the government can offer tailored policy guidance based on a city’s CEE (Liu et al., 2023a).

Additionally, the study introduces an evolutionary model to analyze the change of CEEI, identifying four distinct evolution types: steady-state oscillatory, progressive, and disruptive modes. The results of the GFZ-CUA reveal that progressive mode and oscillatory mode are more common, accounting for 37.50% and 25.00% of the cities, respectively. Chaozhou, Zhangzhou, and Lishui are classified as progressive cities, showing considerable growth in CEE as they transitioned from type IV to type I and from type III to type II. As a result, it is essential to concentrate on these model cities for regulating energy conservation and emission reduction in the construction industry.

Certainly, the research framework for assessing CEEI can be extended to other regions. By applying similar methodologies and frameworks to different geographic areas, researchers can gain broader insights into carbon emission patterns, efficiency improvements, and opportunities for sustainable transformation in the construction industry. This approach has the potential to contribute valuable insights not only to the specific regions under study but also to the broader field of sustainable construction and environmental management.

Conclusion

During the development of the urban construction industry, local governments, enterprises, and social organizations have sought to implement effective measures to enhance CEEI continuously. Nevertheless, the CEEI has distinct developmental features and evolution rules. Therefore, exploring differentiated and scientific

ways to improve the CEECI requires a thorough understanding of its characteristics and rules, as well as a clarification of its possible evolution mode path for type and efficiency. This study establishes assessment criteria for CEECI from both inputs-outputs, perspective. It evaluates the efficiency index using the DEA and Malmquist index model to analyze static-dynamic characteristics. At the same time the evolutionary pattern is introduced to identify the periodic law of CEE. The main conclusions are summarized as follows:

- (1) From both spatial and temporal perspectives, the CEECI in the GFZ-CUA exhibited an overall fluctuating growth trend between 2013 and 2022. The comprehensive and decomposition efficiencies of the construction industry in the region exhibit spatial variation, with a noticeable increase from west to east. The distribution was uneven, displaying clear spatial clustering. More efficient cities were primarily concentrated in provincial capitals and coastal areas, such as Xiamen and Quanzhou, while less efficient cities, such as Nanping and Longyan, were mostly located in the interior.
- (2) The TFP of CEECI in the GFZ-CUA displayed a consistent growth trend. However, the SEC showed a limited impact on the improvement of CEECI, suggesting that technological upgrading serves as the primary driver of current emission reductions. Further examination of decomposition efficiency characteristics revealed that the average values of TFP, EC TC, and PEC all exceeded 1, indicating a positive upward trend.
- (3) CEECI in the GFZ-CUA exhibited notable heterogeneity between 2013 and 2022, reflected in the diversity of city types and evolution modes. Overall, cities were predominantly categorized into the high-efficiency and improved-efficiency types, indicating differences in efficiency levels yet a general trend of improvement across the region. In terms of evolutionary modes, most cities were characterized by oscillatory and progressive patterns, reflecting the stages of technology diffusion and policy adjustments within the urban agglomeration.

However, there are still some limitations of this study. Firstly, due to constraints in acquiring urban data, the analysis in this study only covers a 10-year period. This limitation introduces heightened uncertainty in the periodic analysis and may not fully capture long-term trends. Secondly, the DEA model does not incorporate the whole life cycle implied carbon emissions of the building and may ignore the real environmental impacts. Therefore, future research should consider supplementing the analysis with additional research periods to enhance accuracy. In addition, the development of hybrid models, such as integrating DEA with machine learning techniques, could be explored to capture the nonlinear evolution of CEE more effectively. This can be achieved by conducting in-depth analyses on technical levels, management ability, and energy structure. It is also important to examine other factors that influence CEE and weight distribution. Finally, the research methodology of the Evolutionary Model can also be extended to the provincial and national levels, or cross-regional comparisons can be carried out to distill the common patterns of low-carbon transition in urban agglomerations to obtain a more comprehensive understanding.

Data availability

Data will be made available on request.

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Author contributions

XL conceptualization, funding acquisition, project administration, supervision, and validation. CL: data curation, validation, investigation, methodology, supervision. GD: data curation, formal analysis, investigation, methodology. YL data curation, supervision. YQ: data curation, formal analysis. BW: data curation, investigation.

Competing interests

The authors declare no competing interests.

Ethical approval

The study does not involve human participants or their data.

Additional information

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Informed consent The study does not involve human participants or their data.



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