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Assessing the evolution and convergence of energy-related carbon emission efficiency in the Yangtze River Economic Belt

Peihao Shi [a,*], Qinghua Huang [b]

[a] School of Economic and Management, Wuhan University, Wuhan, Hubei 430072, China
[b] School of Economics and Management, Southwest University, Chongqing 400715, China

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ABSTRACT

This paper examines the spatiotemporal evolution and convergence of energy-related carbon emission efficiency in the Yangtze River Economic Belt (YREB) using prefecture-level data from 2012 to 2021. Employing the SBM-GML strategy, kernel density estimation, the Dagum decomposition method, and the spatial econometric model, the study identifies three main findings: (1) The energy-related carbon emission efficiency in the YREB demonstrates a phased upward trend, particularly after 2014. (2) Pronounced regional disparities are observed, with downstream areas displaying higher efficiency compared to midstream and upstream regions, driven primarily by notable density variations and intra-regional disparities. (3) The analysis reveals both σ-convergence and β-convergence dynamics, highlighting varied spatial effects across regions. Factors such as economic development, industrial structure, and financial incentives exhibit diverse impacts on efficiency, underscoring substantial heterogeneity. This study offers empirical insights crucial for enhancing energy-related carbon emission efficiency in pivotal economic zones.

1. Introduction

Global climate change has escalated the frequency and intensity of extreme weather events, profoundly affecting ecosystems and human health, thereby posing severe challenges to human survival and development (Cole et al., 2013; Currie et al., 2023; Ebenstein et al., 2015). Improving energy-related carbon emission performance, particularly in China, is paramount for mitigating CO_2 emissions and advancing sustainable development (Dietzenbacher et al., 2012; Jarke and Perino, 2017). The Yangtze River Economic Belt (YREB), encompassing more than 40 % of China's population and economic output, holds pivotal importance in this regard. In essence, enhancing the energy-related carbon emission efficiency in this region not only curtails greenhouse gas emissions but also aligns with the objectives of the Paris Agreement. Therefore, it is both essential and urgent to investigate the dynamic changes, regional disparities, sources, and convergence patterns of energy-related carbon emission efficiency in the YREB.

Energy-related carbon emission efficiency refers to the amount of carbon emitted per unit of energy consumed during economic activities (Hou et al., 2021; Song et al., 2018). While a large bulk of the literature has examined this efficiency at national and provincial levels, the dynamics in key regions remain largely overlooked (Clarke-Sather et al., 2011; Mussini and Grossi, 2015). Furthermore, many studies neglect the influence of resource factors on economic development and energy-related carbon emissions (Gutowski et al., 2013; Zhang et al., 2014), hindering an accurate assessment of efficiency. Additionally, existing works primarily rely on traditionally non-parametric approaches that do not adequately incorporate slack variables, leading to biased measurements (Jin et al., 2018; Ramanathan, 2006; Tone, 2001).

In response to these limitations, this paper focuses on the spatial disparities, distribution dynamics, and convergence of energy-related carbon emission efficiency in the YREB. The analysis begins with the application of the SBM-GML method to assess efficiency. Kernel density estimation is then used to track the dynamic evolution of efficiency, and the Dagum decomposition method is employed to investigate spatial trends and their underlying sources. Furthermore, σ-convergence and β-convergence models are utilized to explore the mechanisms of convergence. The study concludes by offering policy implications designed to raise energy-related carbon emission efficiency in the YREB.

This paper makes three primary contributions. First, it expands the measurement framework for energy-related carbon emission efficiency by integrating water resource use and energy consumption, which many

* Corresponding author.
E-mail addresses: peihaoshi@whu.edu.cn (P. Shi), hqh@swu.edu.cn (Q. Huang).

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studies overlook by focusing solely on capital, labor, and technology (Gutowski et al., 2013; Zhang et al., 2014). Second, this paper employs the SBM-GML strategy for measuring energy-related carbon emission efficiency. Unlike previous literature, which predominantly adopts SBM-DEA models (Liu et al., 2016; Meng et al., 2023), super-efficiency SBM, and NDDF (Cheng et al., 2018; Dong et al., 2022; Wu et al., 2023), the SBM-GML method accounts for proportional changes in input and output variables, thereby avoiding information loss in optimal decision-making units. Lastly, this paper utilizes quantitative models to accurately depict the spatiotemporal evolution and convergence of energy-related carbon emission efficiency. Prior studies typically rely on qualitative descriptions (Cheng et al., 2018; Yu and Zhang, 2021), which do not precisely capture regional disparities. To our knowledge, this is the first study to deploy kernel density estimation and the Dagum decomposition method to illustrate the temporal and regional evolution of energy-related carbon emission efficiency in the YREB, providing valuable insights for future research.

The remainder of this paper is organized as follows: Section 2 reviews the relevant literature; Section 3 details the empirical research design, including methods and data sources; Section 4 presents the measurement results; Section 5 analyzes the spatiotemporal evolution of energy-related carbon emission efficiency in the YREB; Section 6 discusses the convergence features of energy-related carbon emission efficiency in the YREB; and the final section concludes the paper and offers policy implications. Fig. 1 illustrates the empirical analysis framework of this paper.

2. Literature review

An emerging body of literature on energy-related carbon emission efficiency focuses on three primary domains: the measurement of efficiency, the examination of spatiotemporal patterns, and the investigation of convergence.

2.1. Measurement of energy-related carbon emission efficiency

The assessment of energy-related carbon emission efficiency has primarily relied on non-parametric DEA models (Hampf and Rødseth, 2015; Ramanathan, 2006). From a theoretical standpoint, traditional DEA methods, which assume proportional changes in inputs and outputs, encounter challenges when accounting for undesirable outputs (Guo et al., 2024; Tone, 2001). To mitigate these challenges, many studies have adopted the SBM model, which incorporates undesirable outputs in measuring energy-related carbon emission efficiency (Liu et al., 2016; Meng et al., 2023). Nonetheless, the SBM model's efficiency value of 1 can render decision-making units incomparable, leading to information loss. To address this limitation, researchers have turned to super-efficiency SBM and the modified non-radial directional distance function (NDDF) to measure carbon emission performance more effectively (Cheng et al., 2018; Dong et al., 2022; Zhang et al., 2023a).

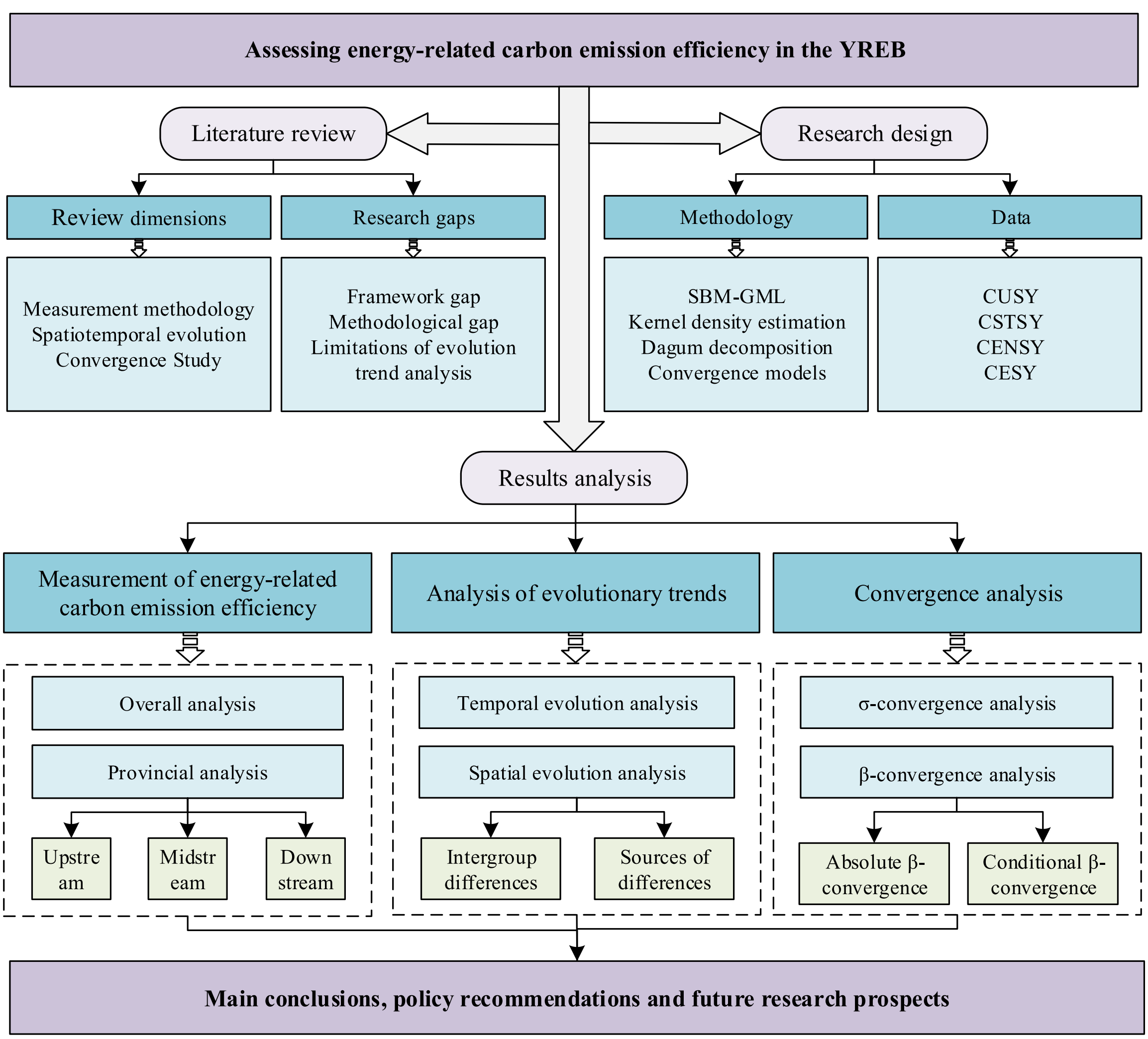

Fig. 1. Analysis framework. *Notes*: CUSY denotes the China Urban Statistical Yearbook, CSTSY represents the China Science and Technology Statistical Yearbook, and CENSY and CESY refer to the China Environmental Statistical Yearbook and the China Energy Statistical Yearbook, respectively.

Additionally, Zhuo et al. (2022) utilized the directional distance function-based ML index and the Global Malmquist-Luenberger (GML) index to estimate urban energy-related carbon emission efficiency.

2.2. Spatiotemporal characteristics of energy-related carbon emission efficiency

The evolution of energy-related carbon emission efficiency over time and across regions has garnered considerable attention in the literature. Temporally, an increasing number of studies employ descriptive analysis to track the evolution of regional carbon emission intensity and identify distinct phases in carbon emissions (Cheng et al., 2018; Meng et al., 2016; Yu and Zhang, 2021). However, fewer studies utilize non-parametric methods to examine the trajectory of regional energy-related carbon emission efficiency. For instance, Zhang et al. (2024) applied kernel density estimation to analyze the temporal evolution of China's energy-related carbon emissions. Spatially, many works have employed the Gini coefficient to measure disparities in energy-related carbon emission efficiency across regions (Mussini and Grossi, 2015; Zhang et al., 2024).

2.3. Convergence of energy-related carbon emission efficiency

The convergence of energy-related carbon emission efficiency has been extensively analyzed using traditional quantitative methods, such as club convergence approaches and conventional panel models (Ezcurra, 2007; Herrerias, 2013). However, spatial spillover effects of economic activities can introduce significant biases in these models when assessing the convergence of energy-related carbon emission efficiency (Bello et al., 2024; Romero-Ávila, 2008). To address this issue, scholars have increasingly adopted spatial econometric models. For instance, Wang et al. (2019) applied a spatial panel strategy to examine provincial-level convergence features, while other studies investigated convergence in specific sectors such as agriculture and industry using spatial econometric approaches (Cui et al., 2022; Dogah and Awaworyi Churchill, 2022; Hu et al., 2024). Furthermore, numerous studies have identified key determinants of energy-related carbon emission efficiency, including economic development scale, industrial structure, household income, and trade openness (Ezcurra, 2007; Zhang et al., 2011).

A comprehensive review of the existing literature reveals several research gaps. First, prior research has disregarded the impact of resource factors on energy-related carbon emission efficiency. Second, many studies have predominantly relied on traditional DEA models to evaluate energy-related carbon emission efficiency, which frequently fail to account for the diverse impacts of various production stages and do not effectively distinguish optimal decision-making units, thereby potentially neglecting technological regressions. Consequently, this leads to notable disparities between measured outcomes and actual production efficiency values. Lastly, existing research commonly focuses on national or provincial scales, thus overlooking nuanced variations in energy-related carbon emission efficiency across different regions. This oversight restricts the depth of insights derived from these studies. To address these gaps, this study concentrates on the YREB as the spatial unit of analysis. Employing the SBM-GML strategy, the research explores spatial disparities, distribution dynamics, and convergence patterns of energy-related carbon emission efficiency within the region.

3. Research design

3.1. Methodology

3.1.1. SBM-GML strategy

Leveraging the work of Li et al. (2023), this paper employs the SBM-GML method to measure energy-related carbon emission efficiency in the YREB. Unlike other DEA models, the SBM-GML model incorporates the adverse effects of undesirable outputs in economic activities on carbon emission efficiency. It effectively resolves the radial and angular issues inherent in traditional DEA models, ensuring global comparability of the production frontier. Consequently, the SBM-GML model has gained increasing acceptance in academic research (Dong and Xu, 2024; Wang and Luo, 2023). Specification (1) presents the mathematical formulation of the SBM-GML strategy.

$$GML_t^{t+1} = \frac{1 + \overrightarrow{S_V^G}\left(x^t, \quad y^t, b^t; g^x, g^y, g^b\right)}{1 + \overrightarrow{S_V^G}\left(x^{t+1}, \quad y^{t+1}, b^{t+1}; g^x, g^y, g^b\right)} \tag{1}$$

In this context, $\overrightarrow{S_V^G}(x^t, y^t, b^t; g^x, g^y, g^b)$ denote the SBM directional distance functions for the overall period, constructed utilizing non-radial and non-angular methods. The detailed calculation methods can be found in Appendix 1 of the Supplementary Information. The result of GML exceeding 1 indicates an enhancement in energy-related carbon emission efficiency in the YREB, whereas a result below 1 suggests a decline. A result equal to 1 signifies no change in energy-related carbon emission efficiency in the YREB.

Following the available literature (Cheng et al., 2020; Li and Lin, 2015; Teng et al., 2021; Yao et al., 2015), this paper establishes a framework of input indicators encompassing capital, labor, technology, and resource elements. Additionally, this paper develops a set of output indicators to evaluate energy-related carbon emission efficiency, considering both economic benefits and energy emissions. Table A1 in the Supplementary Information presents the specific evaluation criteria.

3.1.2. Kernel density estimation

Following Zhang et al. (2024), this study employs kernel density estimation to analyze the temporal trends in energy-related carbon emission efficiency within the YREB. This method typically assumes the density function of random variables as follows:

$$f(x) = \frac{1}{Nh}\sum_{i=1}^{N} K\left(\frac{X_i - \overline{x}}{h}\right) \tag{2}$$

In Eq. (2), N represents the sample size, h denotes the bandwidth of the kernel density function, X_i indicates independently and identically distributed observations, $\overline{x}$ is the mean value, and K stands for the kernel density. Essentially, kernel density estimation operates as a weighted process, typically adhering to the conditions outlined in Eq. (3).

$$\begin{cases} \lim_{x\to\infty} \mathrm{K}(x) \times x = 0 \\ K(x) \geq 0 \qquad \int_{-\infty}^{+\infty} K(x)dx = 1 \\ \sup \mathrm{K}(x) < +\infty \qquad \int_{-\infty}^{+\infty} K^2(x)dx < +\infty \end{cases} \tag{3}$$

Based on Wu et al. (2016), this study utilizes the Gaussian kernel function to examine the temporal dynamics of energy-related carbon emission efficiency in the YREB. The kernel density curves derived from these estimations provide a clear depiction of the distributional characteristics of the variables, highlighting their location, shape, and dispersion.

3.1.3. Dagum decomposition

This paper employs the method of Dagum decomposition to analyze variations in energy-related carbon emission efficiency across the YREB, including its upper, middle, and lower reaches. The advantage of using the Dagum decomposition method lies in its ability to break down regional disparities into three distinct components: intra-regional disparities, inter-regional disparities, and over-density variations (Lv et al., 2021; Zhang et al., 2023b; Zhou et al., 2023). Specification (4) demonstrates the formula for the entire Dagum coefficient.

$$G = \frac{\sum_{j=1}^{k}\sum_{h=1}^{k}\sum_{r=1}^{n_h}\left|y_{ji} - y_{hr}\right|}{2n^2\mu} \tag{4}$$

In Eq. (4), k represents the number of regions, set to 3. n denotes the total number of prefecture-level cities within the YREB. y_{ji} and y_{hr} are the energy-related carbon emission efficiency of the city *i(r)* in region *j(h)*, respectively. μ is the average energy-related carbon emission efficiency of all cities. Eq. (5) provides the formula for computing the Gini coefficient for region *j*.

$$G_{jj} = \frac{\sum_{i=1}^{n_j}\sum_{r=1}^{n_j}\left|y_{ji} - y_{jr}\right|}{2n_j^2\overline{Y_j}} \tag{5}$$

Eq. (6) presents the formula for calculating the Gini coefficient across various regions:

$$G_{jh} = \frac{\sum_{i=1}^{n_j}\sum_{r=1}^{n_h}\left|y_{ji} - y_{hr}\right|}{n_j n_h\left(\overline{Y}_j + \overline{Y}_h\right)} \tag{6}$$

In Eq. (6), j and h represent distinct regions, while n_j and n_h indicate the number of prefecture-level cities in regions *j* and *h*, respectively. $\overline{Y}_j$ and $\overline{Y}_h$ denote the respective average energy-related carbon emission efficiency within regions *j* and *h*.

Finally, this paper decomposes the overall Gini coefficient G into three components: intraregional inequality G_w, interregional inequality G_b, and over-variation density G_t. Specifications (7), (8), and (9) outline the detailed decomposition methods.

$$G_w = \sum_{j=1}^{k} G_{jj} p_j s_j \tag{7}$$

$$G_b = \sum_{j=2}^{k}\sum_{h=1}^{j-1} G_{jh} D_{jh}\left(p_j s_h + p_h s_j\right) \tag{8}$$

$$G_t = \sum_{j=2}^{k}\sum_{h=1}^{j-1} G_{jh}\left(1 - D_{jh}\right)\left(p_j s_h + p_h s_j\right) \tag{9}$$

In Eqs. (7), (8), and (9), the formulas for calculating p_j, s_j, and D_{jh} are as detailed in Eqs. (10), (11), and (12):

$$p_j = n_j / n \tag{10}$$

$$s_j = \frac{n_j \overline{Y_j}}{n\mu} \tag{11}$$

$$D_{jh} = \frac{d_{jh} - p_{jh}}{d_{jh} + p_{jh}} \tag{12}$$

In this context, p_j represents the proportion of cities in region *j* relative to the total number of prefecture-level cities in the YREB. D_{jh} indicates the relative influence on energy-related carbon emission efficiency between regions *j* and *h*, where d_{jh} is the expectation of number where y_{ji} - $y_{hr} > 0$. Similarly, p_{jh} stands for the expectation number of instances where y_{ji} - $y_{hr} < 0$ in regions *j* and *h*, as detailed in Eqs. (13) and (14). F denotes the cumulative density function for regional energy-related carbon emission efficiency.

$$d_{jh} = \int_0^{\infty} dF_j(y)\int_0^{y}(y - x)dF_h(x) \tag{13}$$

$$p_{jh} = \int_0^{\infty} dF_h(y)\int_0^{y}(y - x)dF_j(x) \tag{14}$$

3.1.4. Convergence strategy

In line with the existing literature (Luo et al., 2023; Nie and Lee, 2023; Pan and Li, 2023), this study initially takes advantage of the coefficient of variation (CV) to assess σ-convergence in energy-related carbon emission efficiency within the YREB. The detailed calculation procedure is presented in Eq. (15).

$$\sigma = \frac{\sqrt{\sum_{i}^{n_j} Clog_{ij} - \overline{Clog_{ij}} / n_j}}{\overline{Clog_{ij}}} \tag{15}$$

In this context, *j* is the YREB and its subregions, while *i* is a city in the YREB and its subregions. n_j signifies the number of provinces within each economic zone, and $\overline{Clog_{ij}}$ is the average energy-related carbon emission efficiency across different regions of the YREB.

Building on the existing literature (Bai et al., 2019; Huang et al., 2020; Li and Lin, 2015), this study employs panel modeling, as specified in Eq. (16), to analyze absolute β-convergence.

$$\ln\left(\frac{Clog_{i,t+1}}{Clog_{i,t}}\right) = a_1 + a_2\ln\left(Clog_{i,t}\right) + \rho w_{ij} y_{t+1} + \theta w_{ij}\ln\left(Clog_{i,t}\right) + \mu_i + \eta_t + \varepsilon_{it} \tag{16}$$

where *Clog* $_{i,t+1}$ and *Clog* $_{i,t}$ are the energy-related carbon emission efficiency of the city *i* in the YREB for years *t*+*1* and *t*, respectively. a_2 is the parameter of interest. A notably negative value of a_2 signifies σ-convergence in energy-related carbon emission efficiency in the YREB. w_{ij} represents the economic spatial weight matrix. Additionally, μ_i and η_t correspond to spatial and temporal effects, respectively, while ε_{it} stands for the disturbance term.

Moreover, this study expands upon the absolute convergence model by developing a conditional β-convergence model. Eq. (17) displays the detailed formulation.

$$\begin{aligned}\ln\left(\frac{Clog_{i,t+1}}{Clog_{i,t}}\right) &= a_1 + a_2\ln\left(Clog_{i,t}\right) + aControl_{i,t} + \rho w_{ij} y_{t+1} + \\ &\quad \theta_1 w_{ij}\ln\left(Clog_{i,t}\right) + \theta_2 w_{ij} Control_{i,t} + \mu_i + \eta_t + \varepsilon_{it}\end{aligned} \tag{17}$$

In Eq. (17), $Control_{i,t}$ denotes the set of control variables, with a_2 denoting their associated coefficients. In line with existing literature (Li and Lin, 2015; Wang et al., 2022; Yang et al., 2016b), this study controls for the following variables: economic development (PGDP), industrial structure (STRUC), degree of openness (FDI), marketization level (MSTU), and government financial capacity (GOV).

3.2. Data sources

This study empirically examines the energy-related carbon emission efficiency of the YREB from 2012 to 2021. The data for this study primarily come from various editions of the China Urban Statistical Yearbook, China Statistical Yearbook on Science and Technology, China Environmental Statistical Yearbook, and China Energy Statistical Yearbook, as well as from the statistical yearbooks of the provinces along the YREB. In line with Schafer and Olsen (1998) and Zhou et al. (2019), this study employs the robust linear interpolation method to address missing values, utilizing the simputation package in R. This method effectively preserves overall data trends and patterns, making it suitable for diverse datasets and more accurately reflecting interrelationships within the data, thus gaining widespread adoption.

4. Analysis of energy-related carbon emission efficiency in the YREB: 2012–2021

This paper takes advantage of the SBM-GML strategy to analyze the performance of energy-related carbon emission efficiency in the YREB from 2012 to 2021. The results, illustrated in Fig. 2, depict the energy-related carbon emission efficiency across four selected years: 2012, 2015, 2018, and 2021. The findings indicate a notable improvement in energy-related carbon emission efficiency in the middle and lower regions of the Yangtze River, including Shanghai, Jiangsu, Anhui, and Hubei. However, there remains a need to boost energy-related carbon emission efficiency in the upstream areas, particularly in Yunnan and

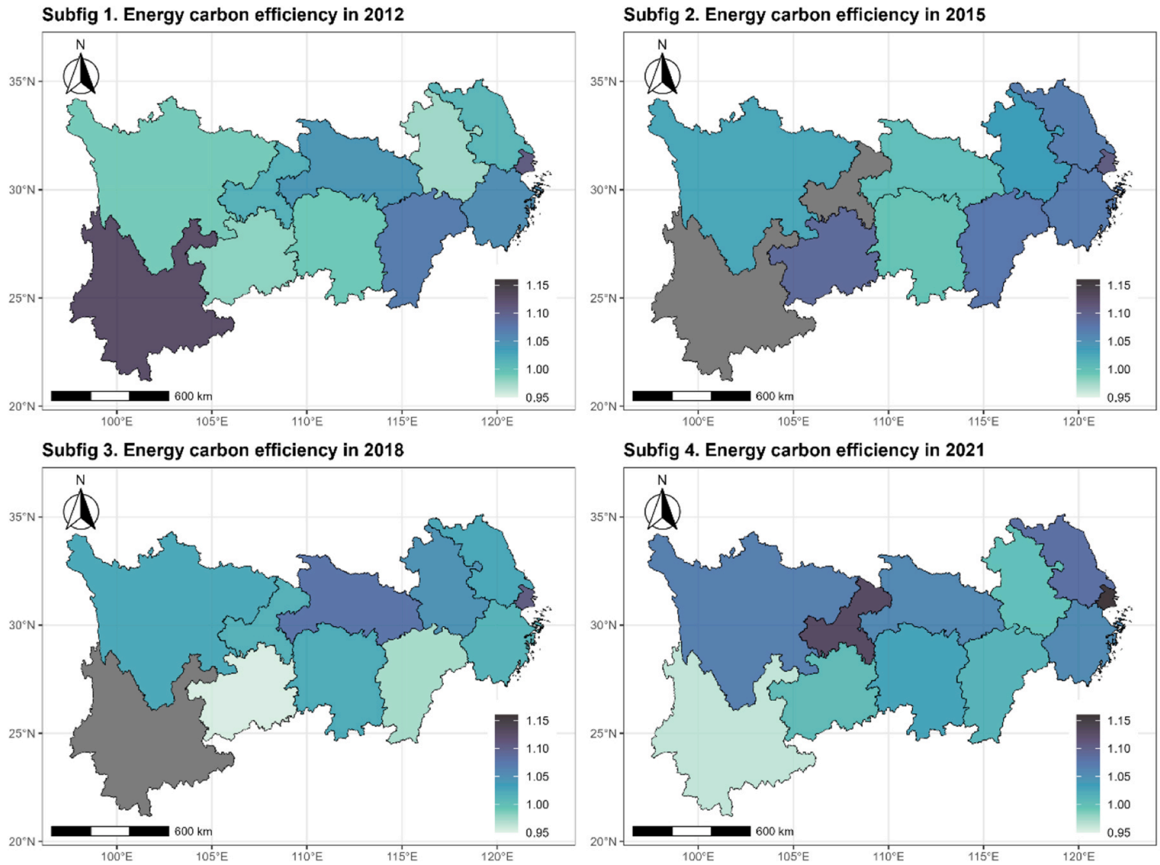

Fig. 2. Energy-related carbon emission efficiency in the YREB.

Guizhou.

This study advances the literature by refining the measurement framework and methodologies for evaluating energy-related carbon emission efficiency. While Liu et al. (2016) utilized the SBM model to assess carbon emission efficiency by focusing on inputs such as capital, labor, technology, and energy consumption, this study offers a novel approach by incorporating water consumption and land use into the measurement framework. This integration enhances the evaluation of energy-related carbon emission efficiency by incorporating additional natural resource variables. Furthermore, the adoption of the SBM-GML index in this paper addresses issues of non-transitivity inherent in traditional DEA models and overcomes feasibility limitations in linear programming. These methodological advancements significantly improve the precision of the measurement process (Li et al., 2023; Oh, 2010).

Fig. 3 displays the overall and regional variations in energy-related carbon emission efficiency in the YREB. In Subfig. 1, a fluctuating upward trend is observed in the energy-related carbon emission efficiency of the YREB, with distinct phase alterations. Until 2014, energy-related carbon emission efficiency in the YREB was on a declining trajectory. Subsequently, there was a distinct increase in efficiency from 2014 to 2017, followed by a downturn from 2017 to 2020. Starting in 2020, the energy-related carbon emission efficiency of the YREB began to recover, exhibiting an upward trend. Possible reasons include the Chinese government's elevation of the YREB development to a national strategic priority in 2014, which enhanced collaborative governance across the region. This led to significant improvements in environmental regulations and subsequent gains in energy-related carbon emission efficiency after 2014. However, post-2017, the slowdown of China's economy resulted in increased industrial carbon emission intensity in specific areas, causing a decline in the energy-related carbon emission efficiency of the YREB from 2017 to 2020.

The YREB can be segmented into three regions based on its geographic features: the lower, middle, and upper reaches. The lower reaches include Shanghai, Jiangsu, Zhejiang, and Anhui; the middle reaches encompass Jiangxi, Hubei, and Hunan; and the upper reaches consist of Chongqing, Sichuan, Yunnan, and Guizhou. Analyzing these regions reveals the following insights: First, the trends of energy-related carbon emission efficiency in the lower, middle, and upper reaches align with the overall trend, highlighting notable improvements since 2014. Second, the lower reaches of the Yangtze River exhibit higher energy-related carbon emission efficiency compared to the middle and upper reaches. Third, the middle reaches exhibit greater fluctuations in energy-related carbon emission efficiency than the upper and lower reaches, particularly noticeable in 2020.

Subfigs. 2–4 of Fig. 3 present the variations in energy-related carbon emission efficiency for the upper, middle, and lower reaches of the YREB. Subfig. 2 highlights Shanghai's dramatically higher energy-related carbon emission efficiency compared to other provinces. Notably, Anhui exhibits comparatively lower energy-related carbon emission efficiency, with substantial year-to-year fluctuations. Subfig. 3 showcases fluctuations in energy-related carbon emission efficiency within the middle reaches of the YREB, ranging from 0.94 to 1.08, indicating considerable annual variations. Similarly, Subfig. 4 illustrates that Chongqing and Sichuan possess relatively higher energy-related carbon emission efficiency in the upper reaches of the YREB. Chongqing, in particular, experiences more pronounced variations, while both regions exhibit rapid improvement, especially after 2017.

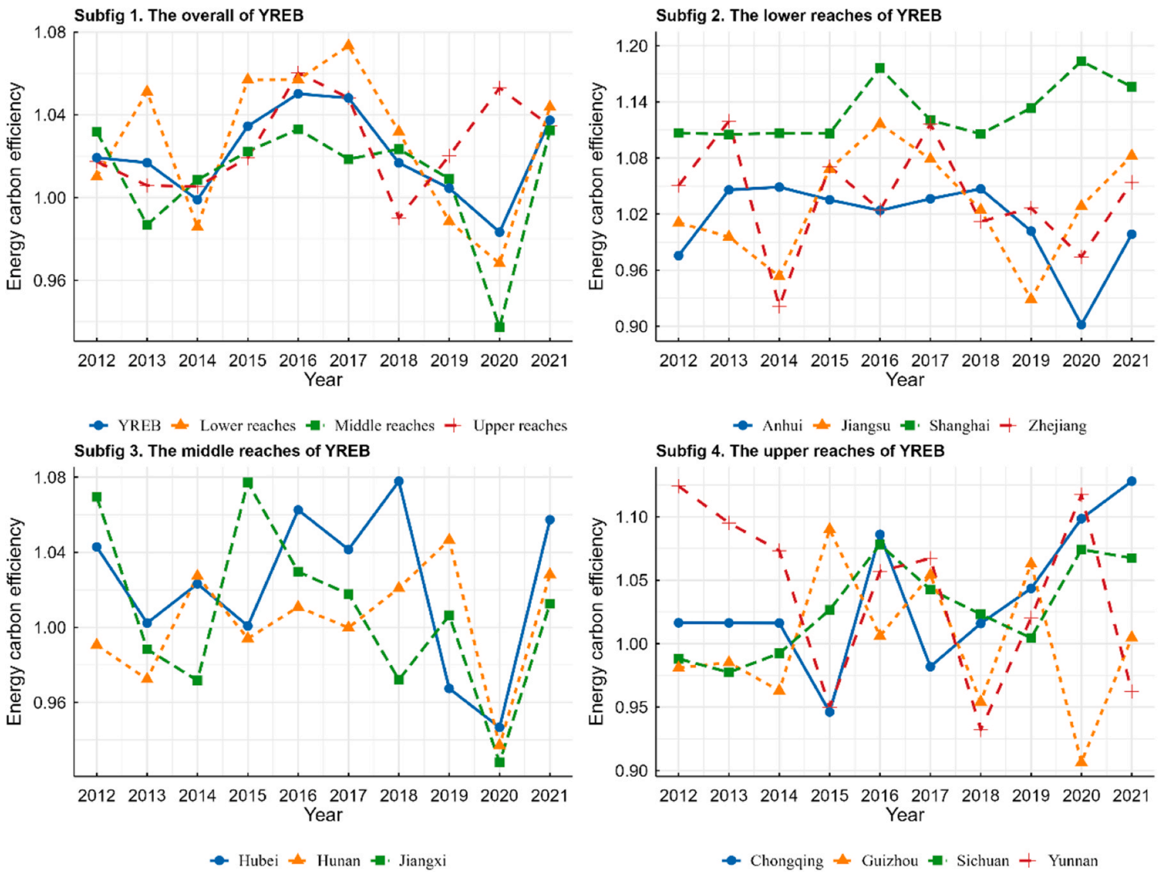

Fig. 3. Energy-related carbon emission efficiency in sub-regions of the YREB.

5. Analysis of the evolutionary trends in energy-related carbon emission efficiency

5.1. Analysis of temporal evolutionary trends

This section employs a kernel density strategy to analyze the dynamic evolution of disparities in energy-related carbon emission efficiency across the entire YREB and its constituent regions. Specifically, it examines distributional features, including location, shape, spread, and polarization. Fig. 4 visually presents the results of kernel density estimation for energy-related carbon emission efficiency in the YREB, as well as in its upper, middle, and lower regions.

From 2012–2021, the distribution curve of energy-related carbon emission efficiency in the YREB has shifted markedly to the right, indicating a consistent increase in efficiency. This rightward shift is observed across the upper, middle, and lower reaches of the YREB, suggesting a gradual improvement in efficiency over time. These findings imply that the resource-intensive utilization in the YREB has strengthened during the study period, leading to continuous enhancements in energy-related carbon emission efficiency.

Regarding distributional shape, the main peak height of the overall distribution curve in the YREB decreases slightly while its width expands significantly, indicating a widening of absolute variances in efficiency. In the lower reaches, the decrease in main peak height is relatively small, and the width narrows, suggesting a reduction in absolute disparities in energy-related carbon emission efficiency. Conversely, in the middle and upper reaches, the peak height of the distribution curve declines, accompanied by a slight expansion in width, indicating amplified disparities in energy-related carbon emission efficiency among these regions.

From the perspective of dispersion, both the overall and regional distribution curves in the YREB exhibit pronounced right-skewed features in energy-related carbon emission efficiency, with notable variations in dispersion among regions. Overall, the variability in energy-related carbon emission efficiency across the YREB shows a decreasing trend, indicating a narrowing gap between cities with higher efficiency and the average level. Specifically, the lower and middle regions display a clear trend of decreased dispersion, while the upper area experiences a slight expansion, suggesting a diminishing gap between cities with higher efficiency and the average level in the middle and lower reaches, albeit with a slight widening observed upstream.

Regarding polarization, from 2012 to 2021, the distribution curves for both the overall YREB and its lower reaches transitioned from a unimodal to a bimodal pattern, with varying degrees of polarization across regions. The overall distribution of energy-related carbon emission efficiency in the YREB exhibits relatively low polarization, peaking in 2018 before evolving into a bimodal curve by 2021. This shift reflects a trend towards multi-polarization in the region's energy-related carbon emission efficiency, accompanied by significant internal variation. In contrast, the upper and middle reaches of the YREB maintain pronounced unimodal patterns, indicating reduced regional disparities. Conversely, the lower reaches experience a shift from a unimodal to a bimodal distribution, signifying intensified multi-level differentiation and enhanced regional variation.

5.2. Analysis of spatial evolution trends

Kernel density functions adequately capture the temporal trends in energy-related carbon emission efficiency within the YREB. However, they do not scrutinize the regional variations in the trajectory of energy-related carbon emission efficiency. Hence, this paper exploits the Dagum coefficient and decomposition method for precise measurement and analysis.

Fig. 5 clearly illustrates Dagum coefficients for energy-related carbon

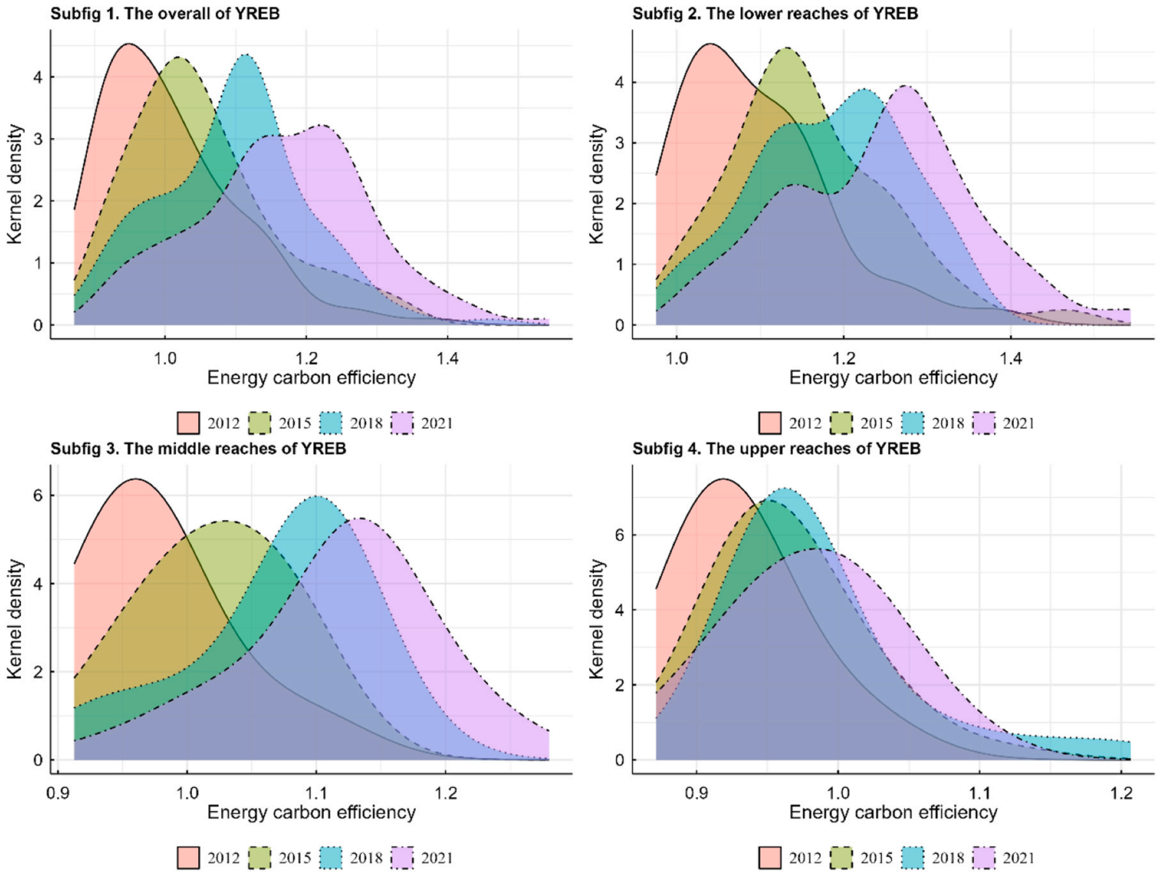

Fig. 4. Evolution trend of energy-related carbon emission efficiency in the YREB.

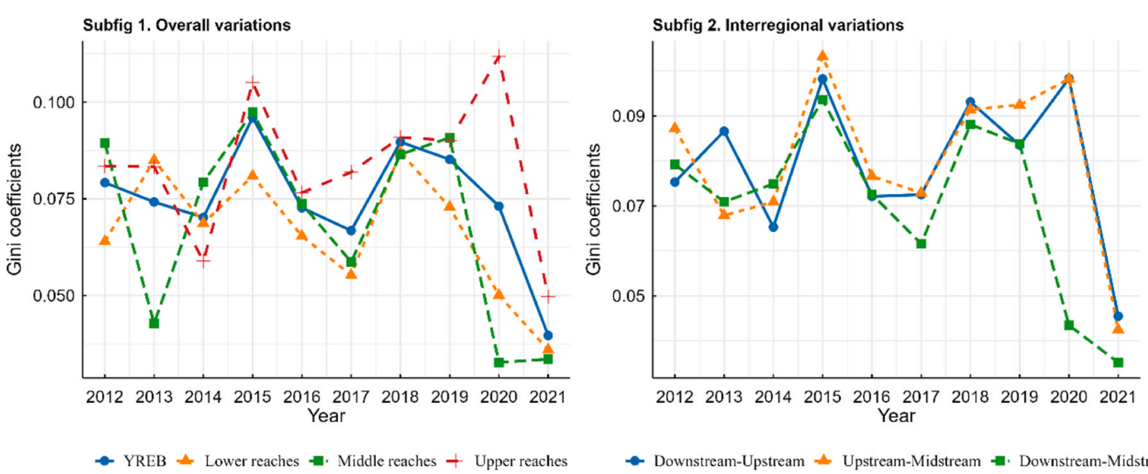

Fig. 5. The disparity in energy-related carbon emission efficiency in the YREB.

emission efficiency in the YREB. Subfig. 1 delineates variations across the YREB, including its upper, middle, and lower reaches. Prior to 2018, the mean of the Dagum coefficient for energy-related carbon emission efficiency in the YREB exhibited stability, remaining around 0.075. From 2018 onwards, there was a notable decrease, dropping from 0.0897 in 2018–0.0397 in 2021. The mean of the Dagum coefficient in the lower reaches displayed relatively modest oscillations, ranging from 0.036 to 0.085, suggesting a "polarization-dispersion effect" that mitigated disparities in energy-related carbon emission efficiency among cities in the lower region. Conversely, the middle and upper reaches featured elevated Dagum coefficients, with mean values of 0.0685 and 0.0832 throughout the study period, indicating a significant disparity in energy-related carbon emission efficiency and an expanding developmental gap between these areas.

Subfig. 2 highlights variations in energy-related carbon emission efficiency among the upper, middle, and lower reaches of the YREB. The most pronounced disparities in efficiency are observed between the lower and upper reaches, with an average coefficient of 0.0790 from 2012 to 2021. Additionally, there is a general upward trend in the disparity between the lower and middle reaches, except in 2021. The lowest disparity levels are recorded between the lower and middle regions of the YREB, showing an overall fluctuating decrease. In 2021, the disparity in energy-related carbon emission efficiency among the upper, middle, and lower reaches reached its lowest point during the study period, accompanied by a significant reduction. This reduction is attributed to an overall decrease in energy-related carbon emission efficiency across YREB regions in 2021.

Subsequently, this study endeavors to explore the sources of disparities in energy-related carbon emission efficiency across the entire YREB, including its upper, middle, and lower segments. Utilizing the Dagum decomposition method, the overall disparities in energy-related carbon emission efficiency are dissected into three components: intra-regional disparities, inter-regional disparities, and inter-regional overlapping density. This method enables a detailed examination of spatial variations in energy-related carbon emission efficiency throughout the YREB. The results of this disparity decomposition are presented in Table 1.

When scrutinizing the origins of these disparities, the intra-regional Gini coefficient within the YREB was 0.0260 in 2012. Subsequently, it follows a distinctive "N" pattern characterized by a decrease, an increase, and another decrease, with values of 0.0311 in 2015 and 0.0296 in 2018. Throughout the study period, the intra-regional Gini coefficient contributes more than 30 % in all years, except for 2020, when it reaches 28.58 %. In the upper, middle, and lower reaches of the YREB, the inter-regional Gini coefficient displays an overall fluctuating upward trend. In 2013, it stood at 0.0146, contributing 19.64 % to the overall disparity. It reaches its peak in 2020, contributing 34.00 % to the overall disparity. The superimposed density reflects the influence of the cross-overlap between the reaches on the overall disparity. Its contribution rate ranges from 37.43 % to 61.16 %, with the most substantial impact on the Gini coefficient of energy-related carbon emission efficiency within the YREB. This study contributes to the exploration of regional variations in energy-related carbon emission efficiency. Building on the methodological approach of Cui et al. (2022), who utilized Theil index decomposition to analyze carbon emission efficiency in China's agricultural sector, this paper expands upon their work by investigating the factors underlying discrepancies in energy-related carbon emission efficiency across different regions.

The variations in energy-related carbon emission efficiency across the upper, middle, and lower regions of the YREB stem from diverse factors. The downstream area, known for its robust economic vitality and innovative prowess, benefits from integrated development that fosters the concentration of innovative elements and expedites structural transformation and industrial upgrading. As a result, there is a marked enhancement in energy-related carbon emission efficiency compared to the middle and upper regions, resulting in significant efficiency disparities (Jin et al., 2018; Zhang et al., 2021). Conversely, the diminished carbon emission efficiency observed in the upper reaches of the YREB can be attributed to several factors. These areas exhibit lower levels of industrialization, characterized by a prevalence of traditional and resource-dependent industries. They remain entrenched in stages marked by high carbon emissions, intensive energy consumption, and comparatively lower income levels, thereby contributing to reduced carbon emission efficiency and slower developmental progress relative to the middle and lower reaches (Li et al., 2022a).

Table 1
The dagum decomposition of energy-related carbon emission efficiency in the YREB.

Year	Intra-group Gini coefficient,		Inter-group Gini coefficient		Super variational density	
	Value	Ratio	Value	Ratio	Value	Ratio
2012	0.0260	32.79 %	0.0048	6.05 %	0.0484	61.16 %
2013	0.0243	32.68 %	0.0146	19.64 %	0.0354	47.68 %
2014	0.0234	33.33 %	0.0053	7.58 %	0.0415	59.09 %
2015	0.0311	32.41 %	0.0085	8.86 %	0.0564	58.73 %
2016	0.0239	32.88 %	0.0057	7.78 %	0.0431	59.34 %
2017	0.0213	31.96 %	0.0118	17.74 %	0.0336	50.29 %
2018	0.0296	33.03 %	0.0088	9.79 %	0.0513	57.18 %
2019	0.0280	32.83 %	0.0071	8.38 %	0.0501	58.80 %
2020	0.0209	28.58 %	0.0248	34.00 %	0.0274	37.43 %
2021	0.0131	32.94 %	0.0025	6.41 %	0.0241	60.65 %

6. Convergence analysis of energy-related carbon emission efficiency in the YREB

6.1. Analysis of σ-convergence

Fig. 6 presents σ-convergence outcomes for evaluating energy-related carbon emission efficiency in the YREB using the CV strategy. Across the study period, the overall coefficient of variation for energy-related carbon emission efficiency in the YREB decreased from 0.1535 in 2012–0.0975. While there were sporadic increases in 2018 and 2019, the general trend was a reduction (see Table A2 in the Supplementary Information). When examining sub-regions, the lower reaches of the YREB experienced a decrease in the coefficient of variation for energy-related carbon emission efficiency, dropping from 0.1317 in 2012–0.0956 in 2021 after an initial increase. This decrease was more pronounced compared to the middle and upper reaches. The middle reaches displayed a higher coefficient of variation, decreasing from 0.1677 to 0.0892. It exhibited a fluctuating decrease, especially after 2019. Conversely, the upper reaches observed its coefficient of variation decrease from 0.1658 in 2012–0.1107. Yet, it showed larger values after 2018, indicating an overall increasing trend. By and large, the coefficient of variation for energy-related carbon emission efficiency in the YREB, as well as in the middle and downstream regions, demonstrated an alternating pattern of decrease and increase. End-of-period values markedly decreased compared to initial values, indicative of a σ-convergence pattern. Notably, the upper reaches did not display σ-convergence features.

6.2. β-convergence analysis

6.2.1. Absolute β-convergence analysis

Table 2 reports the results of the absolute β-convergence analysis for energy-related carbon emission efficiency in the YREB, including its upper, middle, and lower segments. Columns (1)-(4) show statistically significant β-convergence coefficients for energy-related carbon emission efficiency in the YREB and its respective segments, all significant at the 1 % level. These findings indicate the presence of absolute β-convergence, suggesting that regional disparities in energy-related carbon emission efficiency within the YREB are diminishing under comparable conditions, such as population density, industrial structure upgrading, marketization level, and fiscal capacity. Furthermore, examining the magnitude of the convergence coefficients reveals that the middle reaches exhibit the highest coefficient of absolute β-convergence, followed by the upper reaches. Both of these coefficients exceed the overall coefficient for the YREB, implying that the middle reaches are experiencing the fastest convergence in energy-related carbon emission efficiency. This trend indicates that the middle and upper reaches are intensifying their efforts to enhance energy utilization efficiency and reduce regional development disparities.

6.2.2. Conditional β-convergence analysis

Table 3 presents the convergence analysis of energy-related carbon emission efficiency in the YREB, incorporating factors such as population density, industrial structure upgrading, openness, marketization, and fiscal capacity. Employing the Spatial Durbin Model (SDM), analogous to the absolute β-convergence assessment, we derive the following conclusions from columns (1)-(4): First, the coefficients of β-convergence for the YREB and its upper, middle, and lower reaches exhibit a remarkably inverse relationship at the 1 % level, suggesting a conditional β-convergence trend uniformly applicable across all segments within the YREB. This suggests that, beyond initial conditions, various

Fig. 6. σ-convergence of energy-related carbon emission efficiency in the YREB.

influential factors lead to the convergence of energy-related carbon emission efficiency toward equilibrium levels in both the YREB and its constituent regions. Second, the middle reaches feature the highest absolute β-convergence coefficient, surpassing the overall coefficient for the YREB. This highlights a more intensive effort to reduce carbon emissions in the middle segment, consistent with the findings of Yu et al. (2019).

Possible rationales for this phenomenon include local governments facing rigorous environmental assessments, which prompt enterprises with high energy consumption and carbon emissions to actively adopt and innovate green and low-carbon technologies, thereby improving carbon emission efficiency. In essence, government initiatives aimed at enhancing the innovation and deployment of low-carbon technologies have driven cities within the YREB towards higher levels of convergence in energy-related carbon emission efficiency.

In the comprehensive regression model of the YREB, the estimates for both FDI and MSTU lack statistical significance, suggesting that current levels of industrialization and market competition have a limited impact on energy-related carbon emission efficiency in the region. In contrast, the estimated coefficient for PGDP is highly significant ($p < 0.01$), indicating that increased regional economic development markedly improves energy-related carbon emission efficiency. When focusing specifically on the middle reaches of the YREB, both PGDP and STRUC are statistically significant and have positive effects. This underscores the potential of elevating economic development and optimizing industrial structure to enhance energy-related carbon emission efficiency in the middle reaches of the YREB, thereby accelerating convergence in the region.

7. Conclusion and implications

Global climate change poses severe challenges to human survival and development (Chaabouni et al., 2016; Dhakal, 2009; Shi and Wang, 2024). Improving energy-related carbon emission performance, particularly in emerging economies like China, is essential for promoting sustainable development (Li et al., 2022b; Mahapatra and Irfan, 2021; Yang et al., 2016a). The YREB, which accounts for over 40 % of China's population and economic output, plays a critical role in the national

Table 2
Absolute β-convergence analysis of energy-related carbon emission efficiency in the YREB.

Variable	(1) Overall	(2) Lower reaches	(3) Middle reaches	(4) Upper reaches
LClog	−1.247***	−1.194***	−1.296***	−1.248***
	(−39.905)	(−23.057)	(−24.841)	(−21.200)
Spatial rho	−0.037	0.061	−0.492**	−0.343**
	(−0.470)	(0.521)	(−2.318)	(−2.026)
Variance sigma	0.016***	0.013***	0.014***	0.022***
	(20.893)	(12.903)	(12.000)	(11.225)
City EF	Yes	Yes	Yes	Yes
Year EF	Yes	Yes	Yes	Yes
R^2	0.579	0.529	0.615	0.597

Notes: Values in parentheses represent the associated t-statistics. *, **, and *** indicate statistical significance at the 10 %, 5 %, and 1 % levels, respectively. The YREB is categorized into three regions based on its geographic features: the lower, middle, and upper reaches. The lower reaches include Shanghai, Jiangsu, Zhejiang, and Anhui; the middle reaches encompass Jiangxi, Hubei, and Hunan; and the upper reaches consist of Chongqing, Sichuan, Yunnan, and Guizhou.

Table 3
Conditional β-convergence analysis of energy-related carbon emission efficiency in the YREB.

Variable	(1) Overall	(2) Lower reaches	(3) Middle reaches	(4) Upper reaches
LClog	−1.246***	−1.203***	−1.297***	−1.247***
	(−39.863)	(−23.412)	(−25.163)	(−21.074)
PGDP	0.019***	0.022**	0.031**	−0.005
	(2.665)	(2.463)	(2.398)	(−0.226)
STRUC	0.001	−0.000	0.005**	−0.002
	(0.488)	(−0.024)	(2.151)	(−0.597)
FDI	0.002	−0.001	0.006	0.003
	(0.459)	(−0.114)	(0.661)	(0.320)
MSTU	−0.010	−0.020	−0.009	−0.000
	(−1.185)	(−1.611)	(−0.630)	(−0.021)
GOV	−0.000	0.002*	−0.000	−0.001
	(−0.348)	(1.858)	(−0.425)	(−1.261)
Spatial rho	−0.051	−0.095	−0.788***	−0.535***
	(−0.651)	(−0.701)	(−3.097)	(−2.765)
Sigma	0.015***	0.012***	0.013***	0.021***
	(20.893)	(12.903)	(12.000)	(11.225)
City EF	Yes	Yes	Yes	Yes
Year EF	Yes	Yes	Yes	Yes
R^2	0.527	0.371	0.518	0.485

Notes: Values in parentheses represent the associated t-statistics. *, **, and *** indicate statistical significance at the 10 %, 5 %, and 1 % levels, respectively. The YREB is categorized into three regions based on its geographic features: the lower, middle, and upper reaches. The lower reaches include Shanghai, Jiangsu, Zhejiang, and Anhui; the middle reaches encompass Jiangxi, Hubei, and Hunan; and the upper reaches consist of Chongqing, Sichuan, Yunnan, and Guizhou.

economy. Enhancing the energy-related carbon emission efficiency in this region can protect coastal ecosystems, reduce pollutant inputs, and help China reduce greenhouse gas emissions, thereby supporting the goals of the Paris Agreement.

This study employs city-level data from 2012 to 2021 to examine the current status, spatiotemporal evolution, and convergence of energy-related carbon emission efficiency in the YREB. The key findings are as follows: (1) Energy-related carbon emission efficiency in the YREB exhibits a fluctuating upward trend, with downstream regions generally demonstrating higher efficiency compared to midstream and upstream regions. (2) Significant disparities in energy-related carbon emission efficiency exist across different regions within the YREB, particularly between the midstream and upstream areas. (3) The YREB as a whole, along with its midstream and upstream regions, exhibit σ-convergence features, whereas the downstream region does not. Both absolute and conditional β-convergence are observed across the upstream, midstream, and downstream regions, with varying spatial effects. Moreover, factors such as economic development level, industrial structure, openness to foreign trade, and technological progress significantly influence energy-related carbon emission efficiency, displaying notable heterogeneity across different regions.

The policy implications of this study are threefold. First, promoting industrial transformation and upgrading is crucial to enhancing regional energy-related carbon emission efficiency. The study indicates a rising trend in overall energy-related carbon emission efficiency within the YREB. Policymakers should prioritize the transformation and upgrading of industries in the YREB, aiming to enhance technological equipment and energy utilization rates. Moreover, the midstream and downstream regions of the YREB should accelerate the development of strategic industries to upgrade industrial structures. Second, optimizing interregional industrial cooperation mechanisms is essential for improving energy-related carbon emission efficiency, particularly through facilitating industrial gradient transfers. The study underscores significant disparities in energy-related carbon emission efficiency across different regions within the YREB. Consequently, downstream regions should facilitate the relocation of resource-processing and labor-intensive industries to midstream and upstream regions, thereby fostering an overall green ecological enhancement in the industrial value chain across the YREB. Third, enhancing collaborative innovation capabilities is pivotal for improving factor utilization efficiency. The study identifies technological innovation as a critical factor influencing energy-related carbon emission efficiency. Accordingly, enterprises should strengthen the research, development, and application of green, low-carbon technologies tailored to the carbon emission requirements of the YREB's upstream, midstream, and downstream regions. Through such low-carbon technological innovations, they can expedite the achievement of early carbon peaking and eventual zero-carbon targets.

This study encounters several limitations. Initially, it focuses on energy-related carbon emission efficiency within a prominent region of China. Given the global imperative of environmental conservation, future research could compare energy-related carbon emission efficiency across countries such as India, Brazil, and South Africa, all grappling with substantial environmental challenges. Additionally, while this paper employs the SBM-GML index to evaluate energy-related carbon emission efficiency, it does not delve into the origins of efficiency changes. Subsequent investigations could explore this aspect more deeply using decomposition methods.

CRediT authorship contribution statement

Peihao Shi: Writing – review & editing, Writing – original draft, Supervision, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Qinghua Huang:** Visualization, Validation, Supervision.

Declaration of Competing Interest

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

Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.psep.2024.09.058.

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Peihao Shi is a Ph.D. candidate at the School of Management and Economics, Wuhan University, China. His research interests include Green Innovation, Sustainable Development, and Low-carbon Industrial Development. He has published a corpus of papers, which have been cited over 500 times.

Qinghua Huang is a full professor and vice dean of the School of Economics and Management, Southwest University, China. His research interests include Environmental Policy, Ecological Economics, and Energy Economics. He has published over 100 research papers in prestigious peer-reviewed journals such as *Technological Forecasting & Social Change* and *Environmental Impact Assessment Review*.