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Original Research

Analysis of Spatiotemporal Evolution Characteristics of Carbon Emission Efficiency in the Yangtze River Delta Region Based on Super-Efficiency Slacks-based Measure Data Envelopment Analysis Model

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Abstract

Research on carbon emission efficiency (CEE) is critical for formulating effective climate change mitigation strategies and advancing regional sustainable development. This study provides a comprehensive analysis of the CEE in the Yangtze River Delta (YRD) region, a key economic region in China, from 2012 to 2021. Employing the super-efficiency Slacks-based Measure Data Envelopment Analysis (SBM-DEA) model to measure the static efficiency and the Malmquist index to track dynamic productivity changes, we examine the spatiotemporal evolution across 41 prefecture-level cities. The results indicate that: 1) Temporally, the regional CEE exhibited a fluctuating upward trend with a V-shaped recovery pattern, achieving an overall growth of 5.8% over the decade. 2) Spatially, the efficiency displayed a distinct core-periphery structure, forming significant clusters of high-value and low-value zones. 3) Regionally, a clear hierarchical gradient was observed: Shanghai > Jiangsu > Zhejiang > Anhui, which is strongly correlated with city size and administrative tier. 4) The spatial agglomeration pattern evolved from fragmented, small-scale clusters to more consolidated, large-scale high-high agglomerations. This transition underscores the positive impact of industrial green transformation and regional integration policies within the YRD, offering valuable insights for low-carbon development planning in other urban agglomerations.

Keywords: Super-Efficiency SBM-DEA model, Malmquist Index, carbon emission efficiency, Yangtze River Delta region

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Introduction

Over the past four decades of reform and opening up, China's economy has undergone rapid development, positioning itself as the world's second-largest economy [1]. However, this growth has been accompanied by substantial energy consumption and carbon emissions, making China the largest emitter of carbon globally [2]. In response to the urgent need to combat climate change, General Secretary Xi Jinping, during the 75th UN General Assembly in September 2020, committed to "strive to peak carbon emissions before 2030 and achieve carbon neutrality before 2060" [3]. The report of the 20th National Congress of the Communist Party of China further reinforced the development principle of "steadily advancing carbon peaking and carbon neutrality, and actively engaging in global climate governance". While China has established preliminary policy and technological frameworks to achieve the "dual carbon" goals [4], significant regional disparities in development remain [5]. As a result, exploring differentiated pathways for emission reductions, particularly through enhancing CEE, has become a central focus for both researchers and policymakers.

Extensive empirical research has been conducted on CEE, primarily addressing evaluation metrics, spatiotemporal dynamics, and influencing factors. Existing literature can be categorized into five key themes: First, regarding CEE measurement, studies commonly focus on carbon emission intensity and carbon productivity as core indicators. Methodologies are broadly divided into single-factor evaluation and total-factor framework calculations, each with distinct advantages and limitations [6-8]. Second, concerning the relationship between carbon emissions and economic growth, some studies identify an N-shaped curve, suggesting that economic scale exerts a positive driving effect on emissions [9, 10]. Others observe that carbon intensity follows a slow decline–rapid decline trajectory amid economic expansion, while high-quality economic development correlates with fluctuating CEE trends. Short-term dynamics often exhibit inverted V- or U-shaped patterns, with certain regions even experiencing declines [11-13]. Third, in terms of spatial variation, international research tends to assess CEE across broad spatiotemporal scales to identify optimal production paradigms. For instance, studies of 20 EU members between 1990 and 2003 revealed minimal fluctuations in CEE, identifying environmental technology as the central determinant [14-17]. In contrast, domestic studies in China emphasize finer-scale spatial correlation analyses, indicating a general upward trend accompanied by marked regional disparities – characterized by an eastern > northeastern ≈ central > western gradient – and widening gaps among major strategic zones [18]. Fourth, regarding measurement approaches, international scholars frequently employ multi-factor Data Envelopment Analysis (DEA) and the Metafrontier Non-radial Luenberger method [19], whereas domestic research predominantly utilizes DEA, spatial autocorrelation analysis, and weighted regression techniques [20-22]. Fifth, studies consistently identify technological progress, policy regulation, energy structure, and urbanization level as key drivers of regional disparities in CEE [23-28].

Despite these contributions, significant research gaps persist. Few studies have integrated undesirable outputs and dynamic efficiency evolution within a unified analytical framework, and the mechanisms underlying spatial heterogeneity in CEE remain underexplored. Addressing these limitations, this study takes the Yangtze River Delta (YRD) region as an empirical case and employs NPP/VIIRS nighttime light data to estimate carbon emissions. By combining a super-efficiency SBM-DEA model with the Malmquist index, we systematically analyze the spatiotemporal evolution of CEE from 2012 to 2021. The study introduces several innovations: incorporating remote sensing data to refine emission estimates; developing a dynamic efficiency assessment framework that accounts for non-deterministic outputs; and elucidating the mechanisms driving regional CEE evolution from both temporal and spatial perspectives. Our findings aim to provide a theoretical basis and policy support for the low-carbon transition of the Yangtze River Delta and other developed regions.

Based on the aforementioned research context and existing gaps, this study takes the YRD region as its empirical case to systematically explore the following core questions:

1) What are the spatiotemporal dynamics of CEE in the YRD region from 2012 to 2021?

2) Does the spatial differentiation of CEE exhibit significant agglomeration patterns? What mechanisms drive its evolution?

3) How do regional integration and industrial green transformation influence pathways for enhancing CEE?

By addressing these scientific questions, this study aims to construct an evaluation framework integrating non-expected output and dynamic efficiency, revealing the evolution mechanisms of regional CEE and providing a scientific basis for differentiated emission reduction policies.

Materials and Methods

Overview of the Study Area

The YRD region is one of China's most economically dynamic, open, and innovation-intensive regions, contributing nearly one-quarter of the national GDP and maintaining leading levels of labor productivity. It also hosts multiple national science centers and top universities, forming one of the country's highest-density scientific and educational clusters [29]. Despite these advantages, the region exhibits marked ecological heterogeneity: southern Anhui and the mountainous areas of southwestern Zhejiang possess strong ecological endowments, whereas Jiangsu Province faces more limited ecological capacity [30]. Since the proposal of the YRD Regional Integration Development Demonstration Zone in 2018 [31], the subzone anchored in Qingpu (Shanghai), Wujiang (Jiangsu), and Jiashan (Zhejiang) has become a key platform for promoting integrated, high-quality, and ecologically oriented development (Fig. 1). Strengthening ecological–economic linkages and transforming ecological advantages into drivers of sustainable growth are now central to the region's transition toward a modern green economy. As a pilot area for coordinated ecological civilization construction, the YRD faces pressing challenges related to improving industrial energy efficiency, reducing resource and energy intensity, and curbing carbon and pollutant emissions. This study focuses on the YRD due to its representativeness in China's modernization and green transition: it is one of the country's most economically dense and energy-intensive regions, making changes in its CEE a bellwether for achieving dual-carbon goals. Moreover, its ongoing shift from rapid expansion to high-quality development – characterized by industrial and energy system restructuring – offers an ideal setting for examining CEE dynamics. Insights from the YRD's integration strategy further provide an institutional reference for cross-regional collaborative emission reduction, with implications for policy design in other global urban agglomerations and developing regions such as Asia and South America.

Research Methods

Super-Efficiency SBM-DEA Model

The super-efficiency SBM-DEA model is an advanced non-radial, non-angular data envelopment approach proposed by Tone [32]. Compared with traditional DEA models, the SBM-DEA model incorporates slack variables, allowing for more flexible and accurate evaluations. It measures the comprehensive efficiency of decision-making units (DMUs) (those with an efficiency score of 1), while considering the incomplete utilization of production factors. This approach effectively addresses the problem of redundant inputs inherent in radial DEA models and overcomes the limitation of conventional DEA models that assess efficiency only from the input or output perspective. As an extension of the SBM framework, the super-efficiency SBM model introduces the concept of super-efficiency, enabling DMUs to attain efficiency values greater than 1. This facilitates further differentiation and ranking among efficient DMUs. Its fundamental formulation is as follows: For the *k*-th DMU,

$$\rho = min\frac{1+\frac{1}{m}\sum_{i=1}^{m}\frac{s_i^-}{x_{ik}}}{1-\frac{1}{q+h}\left(\sum_{i=1}^{q}\frac{s_i^g}{y_{ik}^g}+\sum_{i=1}^{h}\frac{s_i^b}{y_{ik}^b}\right)} \tag{1}$$

$$x_{ik} \geq \sum_{j=1,\ j\neq k}^{n}\lambda_j x_{ij} - s_i^-, i = 1,2,\ldots,m; \tag{2}$$

Fig. 1. Administrative divisions of the Yangtze River Delta Region.

$$-y_{uk}^{g} \geq -\sum_{j=1,\ j\neq k}^{n} \lambda_j y_{uj}^{g} - s_u^{g}, u = 1,2,\ldots,q; \quad (3)$$

$$b_{vk}^{b} \geq \sum_{j=1,\ j\neq k}^{n} \lambda_j y_{vj}^{b} - s_v^{b}, v = 1,2,\ldots,h; \quad (4)$$

In the formula, λ represents the weight vector, x denotes the input variables, and y signifies the output variables. The model includes a total of m inputs, s outputs (comprising q desirable outputs and h undesirable outputs), and n DMUs. Specifically, y^g refers to the desirable output, while y^b represents the undesirable output; s^-, s^g, and s^b correspond to the slack variables for inputs, desirable outputs, and undesirable outputs, respectively. The symbol ρ denotes the objective function, that is, the CEE value. When $\rho \geq 1$, the DMU is considered fully efficient, indicating that the optimal output level has been achieved given the available inputs. By contrast, when $\rho < 1$, the DMU is deemed inefficient, implying potential for improvement in resource utilization or output performance.

The super-efficiency SBM-DEA model improves upon traditional DEA by directly integrating input-output slack variables into the objective function, thereby addressing input and output slack issues. It also effectively handles the coexistence of desirable and undesirable outputs in production frameworks. In contrast, the standard SBM model treats all efficient DMUs as equally efficient, without differentiating performance among them. The super-efficiency SBM model overcomes this limitation by permitting efficiency scores greater than 1, enabling comparison among efficient DMUs. These enhancements make the super-efficiency SBM-DEA model particularly suitable for evaluating performance and efficiency across diverse entities, and provide a solid analytical foundation for policy and management decisions. Therefore, in addressing complex measurement tasks such as CEE, the super-efficiency SBM-DEA model offers a more refined and applicable tool.

Malmquist Index Model

Spatial autocorrelation, a core concept in spatial econometrics, serves as an exploratory spatial data analysis tool to describe and quantify the dependence of a geographic phenomenon or attribute across spatial units. It is commonly measured using Global Moran's I and Local Moran's I indices. The global index evaluates the overall significance of spatial autocorrelation across the entire study area, whereas the local index identifies specific locations of spatial clustering when global autocorrelation is significant. Their basic formulations are as follows:

$$I = \frac{n}{S_0} \cdot \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}(x_i-\bar{x})(x_j-\bar{x})}{\sum_{i=1}^{n}(x_i-\bar{x})^2} \quad (5)$$

$$I_i = \frac{(x_i-\bar{x})}{S^2} \sum_{j\neq i}^{n} x_{ij}(x_{ij} - \bar{x}) \quad (6)$$

In the formula, n denotes the total number of spatial units; x_i and x_j represent the observed values of the i-th and j-th spatial units, respectively; w_{ij} indicates the spatial weight between units i and j; and S_0 is the sum of all spatial weights. I represents the calculated Moran's I index. A value of I significantly greater than 0 suggests positive spatial autocorrelation, where similar attribute values cluster together (e.g., high-high or low-low aggregation). A value significantly less than 0 indicates negative spatial autocorrelation, implying a dispersed pattern with dissimilar values between neighbors (e.g., high-low or low-high aggregation). When I is approximately 0, no significant spatial autocorrelation is detected, indicating a random spatial distribution of the data.

Spatial autocorrelation models quantify proximity relationships between geographic units by constructing spatial weight matrices. This approach addresses the limitation of conventional statistical methods that ignore spatial dependence, while also revealing clustered, dispersed, or random spatial patterns in geographic phenomena. While global spatial autocorrelation analysis can only detect the presence of overall spatial dependence, local spatial autocorrelation analysis identifies specific spatial clusters and outliers by calculating the local Moran's I index for each unit. This enables the detection of hotspots, cold spots, and anomalous areas, thereby providing a scientific basis for spatial policy-making and regional planning. Thus, in studies aimed at exploring the spatial distribution patterns and underlying mechanisms of geographic phenomena, spatial autocorrelation models offer a more comprehensive and precise analytical framework.

Data Sources

Nighttime light (NTL) imagery serves as an effective proxy for characterizing the intensity of human activities, which are the primary source of carbon emissions. This established theoretical correlation is well-supported by empirical studies in international literature [33]. Currently, two mainstream NTL datasets are increasingly utilized in analyses of urban structure and in monitoring socioeconomic characteristics throughout urbanization processes [34]. However, differences in spatial resolution, temporal coverage, and sensor performance across these datasets often lead to limited compatibility, constraining their application in long-term time-series analyses. To address this issue, this study integrates the MSP-OLS and NPP-VIIRS NTL datasets using the autoencoder (AE) model proposed by Zuoqi Chen et al. [35]. A regression equation is established between the harmonized NTL values and statistical CO_2 emissions data to derive panel data on carbon emissions for the study period from 2012 to 2021. This integrated approach effectively mitigates the temporal discontinuity associated with single-source NTL datasets, enhances the continuity and accuracy of carbon emission estimates, and provides reliable data support for long-term studies on CEE.

The remaining statistical data used in this study, including year-end employment figures, regional GDP, total fixed-asset investment, energy consumption, and carbon dioxide emissions at the prefecture-level city level, were obtained from the statistical yearbooks and bulletins of the relevant provinces and municipalities in the YRD region, covering the period from 2012 to 2021.

Results

Temporal Characteristics Analysis

Overall Temporal Evolution Characteristics of the YRD Region

This study applies a super-efficient SBM-DEA model incorporating undesirable outputs, along with the Malmquist index, to assess the CEE of prefecture-level units in the YRD region from 2012 to 2021 (Table 1). As summarized in Table 1, the regional averages over this period are 1.044 for the technical efficiency change index (EFF), 0.962 for the technological change index (TEC), and 0.984 for total factor productivity (TFP).

An EFF value greater than 1 reflects relatively effective resource allocation and production management under the existing technological frontier, indicating that actual output levels are close to the production possibility boundary. This result underscores a high degree of operational optimization and scale efficiency across the region. In contrast, a TEC value below 1 point to constrained progress in the innovation and application of carbon mitigation technologies, suggesting that technological advancement was not the main contributor to CEE growth during the study period. The TFP value of 0.984, slightly below 1, implies that overall CEE has yet to reach an optimal state, revealing latent potential for improvement in both factor allocation and technological adoption. Given that TFP comprehensively captures the combined effects of technical efficiency and technological change, it will be employed as

Table 1. Changes in Carbon Emission Technical Efficiency Index, Technological Change Index, and Total Factor Productivity for Cities in the Yangtze River Delta, 2012-2021.

City	EFF	TEC	TFP
Shanghai	1.036	1.143	1.184
Nanjing	1.227	0.928	1.115
Wuxi	1.020	0.994	1.009
Xuzhou	1.117	1.002	1.024
Changzhou	1.284	0.999	1.162
Suzhou (Jiangsu)	0.967	1.004	0.971
Nantong	1.014	0.977	1.019
Lianyungang	1.053	0.924	0.994
Huaian	1.294	0.895	1.159
Yancheng	1.000	0.944	0.970
Yangzhou	1.139	0.885	0.974
Zhenjiang	1.103	1.075	1.109
Taizhou (Jiangsu)	1.058	0.923	1.015
Suqian	1.052	0.981	1.059
Hangzhou	1.205	0.927	1.094
Ningbo	1.138	0.974	1.092
Wenzhou	0.961	0.975	0.938
Jiaxing	1.014	0.937	0.958
Huzhou	1.062	0.931	1.002
Shaoxing	0.845	1.001	0.848
Jinhua	0.863	0.988	0.866
Quzhou	1.011	0.990	0.993
Zhoushan	1.448	0.855	0.968
Taizhou (Zhejiang)	0.963	0.976	0.939
Lishui	0.923	0.984	0.899
Hefei	1.094	1.003	1.097
Wuhu	1.005	0.946	0.936
Bengbu	1.019	0.952	0.948
Huainan	0.995	0.957	0.935
Maanshan	1.003	0.972	0.974
Huaibei	0.944	0.956	0.883
Tongling	0.973	0.962	0.913
Anqing	1.047	0.965	0.992
Huangshan	0.939	0.927	0.837
Chuzhou	1.252	1.037	1.297
Fuyang	0.840	0.928	0.741
Suzhou (Anhui)	0.964	0.918	0.811
Liuan	1.016	0.872	0.884
Bozhou	0.958	0.941	0.905
Chizhou	1.014	0.962	0.973
Xuancheng	0.933	0.934	0.874
Regional mean	1.044	0.962	0.984

Note: The data in the table represent the average values from 2012 to 2021.

the core metric in subsequent analyses to further elucidate the spatiotemporal dynamics of CEE in the YRD.

To further elucidate the evolutionary trajectory of CEE, this study selected four representative time points (2012, 2015, 2018, and 2021) to visualize the temporal variation in TFP across the YRD region (Fig. 2). Overall, TFP exhibited a distinct V-shaped fluctuation, which can be categorized into three phases.

During Phase I (2012-2015), TFP averaged 1.026, reflecting relatively high performance. This was primarily driven by a high average technical efficiency change (EFF) of 1.128, which substantially supported TFP growth. In contrast, the average technological change index (TEC) stood at 0.921, indicating that technological innovation had not yet become the dominant driver of efficiency improvement. These trends align with policy initiatives implemented during this period. For instance, the Action Plan for Energy Conservation, Emission Reduction, and Low-Carbon Development (2014-2015), issued by the General Office of the State Council in May 2014, emphasized regional coordinated emission reduction and greening of transportation systems, contributing to short-term management efficiency gains. Similarly, the 2015 Environmental Performance Report for the 15+1 Cities in the Yangtze River Delta reflects the region's focus on environmental performance and carbon emission control.

In Phase II (2015-2018), TFP declined to an average of 0.842, representing an approximately 18% decrease compared to the previous phase. This downturn was driven by simultaneous declines in both EFF and TEC, which fell by 6% and 11%, respectively. These patterns reflect diminishing marginal returns from earlier management interventions and structural challenges associated with industrial transformation. The decline was particularly evident in heavy industrial cities transitioning toward advanced manufacturing, where emerging industries had not yet developed the capacity to fully replace previous production modes. Additionally, the transfer of high-carbon industries into parts of the study area temporarily suppressed overall CEE. These trends correspond with the implementation of the Yangtze River Delta Urban Agglomeration Development Plan, under which regional industrial restructuring initially led to a temporary reduction in resource allocation efficiency. In Jiangsu and Zhejiang, for example, cities shifting from heavy chemical industries to high-end manufacturing experienced a green transition gap, as emerging sectors had not yet achieved scale economies. Concurrently, Anhui's acceptance of high-carbon industries transferred from other provinces contributed directly to the rise in its carbon emission intensity during this period.

During Phase III (2018-2021), TFP rebounded to an average of 1.086, marking an increase of approximately 29% compared to the preceding phase. This recovery was largely driven by a marked improvement in TEC, which grew by about 37%, signaling that technological innovation had become the key driver of efficiency gains. This shift aligns with several key contextual developments, including the deepening of regional integration, the accelerated deployment of green technologies, and the continuous optimization of the energy structure. It also corresponds with national strategic priorities aimed at advancing green and low-carbon technologies in response to international carbon-related trade barriers. Specifically, amid rising global trade protectionism, developed economies tightened export controls on high-tech products targeting China. This external pressure prompted the YRD to actively restructure its industrial system, with strategic emphasis placed on low-carbon and high-technology sectors. Meanwhile, policy measures outlined in the Integrated Ecological and Green Development Planning of the Yangtze River Delta Demonstration Zone (such as accelerating industrial transformation, establishing collaborative environmental governance mechanisms, and jointly formulating regional environmental plans) began.

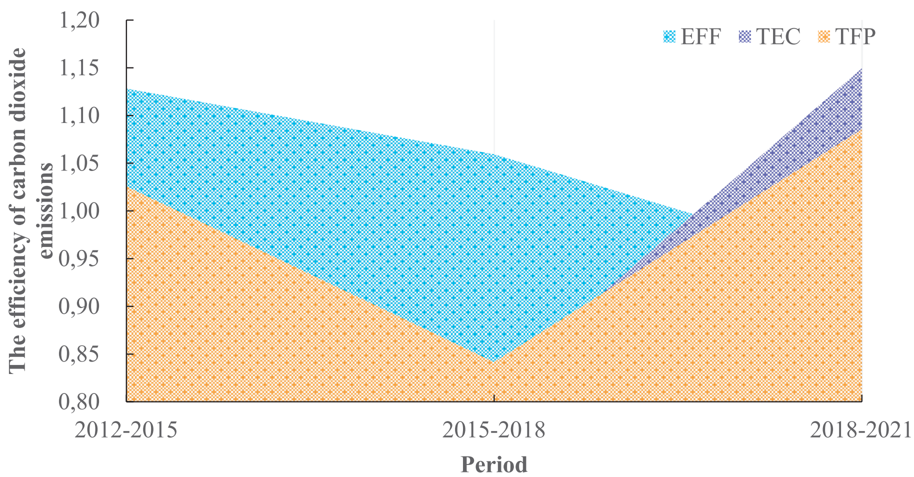


Fig. 2. Trends of carbon emission efficiency in the Yangtze River Delta Region, 2012-2021.

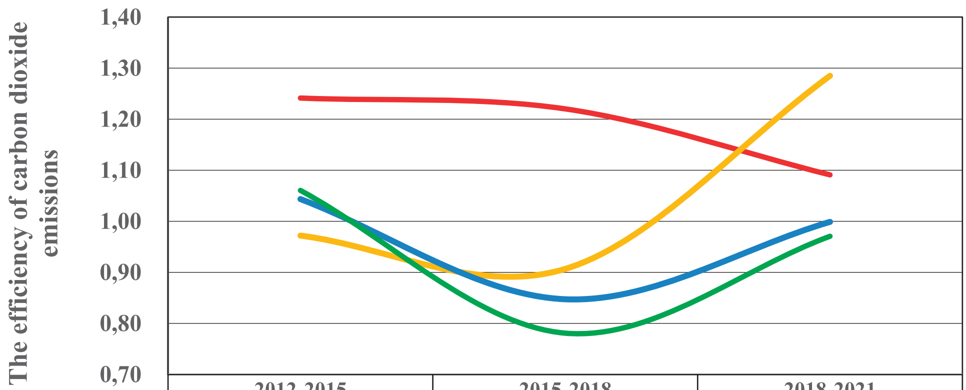
In summary, the evolution of CEE in the YRD demonstrates clear policy responsiveness and technology-driven dynamics. The observed phased fluctuations reflect the complex interplay between structural economic adjustment and the adoption of innovative technologies during the transition toward a low-carbon economy.

From a mechanism perspective, the V-shaped fluctuation in CEE may be closely linked to firms' risk response strategies during the energy transition process. Research indicates that energy structure transformation may temporarily exacerbate operational risks for enterprises [36, 37], leading to a decline in the TEC between 2015 and 2018. However, government interventions through environmental regulations and green subsidies [38, 39] can incentivize firms to adopt low-carbon technologies, driving a significant rebound in TEC from 2018 to 2021. Furthermore, regional resource utilization efficiency and system resilience [40, 41] determine a city's adaptive capacity to transition shocks, thereby influencing the stability of EFF.

Evolutionary Characteristics of One Municipality and Three Provinces

At the provincial level, the CEE of Shanghai, Jiangsu, Zhejiang, and Anhui (collectively known as the "one municipality and three provinces" in the YRD region) exhibited distinct temporal variations from 2012 to 2021 (Fig. 3). The average annual TFP values were 1.184 for Shanghai, 1.055 for Jiangsu, 0.963 for Zhejiang, and 0.937 for Anhui. While Shanghai experienced a gradual decline, the other three provinces displayed V-shaped fluctuation trends, with Jiangsu demonstrating the most pronounced recovery and growth. In detail, Shanghai's CEE decreased from 1.241 in 2012 to 1.091 in 2021, reflecting a decline of approximately 12%. Despite this downward trajectory, its TFP remained consistently above the production frontier (TFP>1), indicating sustained high efficiency levels, albeit with diminishing growth momentum. In contrast, Jiangsu Province recorded a 32% increase in TFP, rising from 0.972 to 1.285, underscoring consistent efficiency improvements. Both Zhejiang and Anhui experienced moderate declines: Zhejiang's TFP decreased from 1.044 to 0.999 (a 4% reduction), while Anhui's fell from 1.061 to 0.971 (an 8% reduction). By the end of the study period, these two provinces remained within a relatively low-efficiency range.

The observed disparities in CEE across the region can be attributed to several underlying factors. Shanghai's moderated efficiency growth likely reflects constraints such as slowing urban renewal, industrial path dependence, and a mismatch in low-carbon technology talent. As a highly developed economy, its traditional energy-intensive sectors face elevated institutional and technological transition costs. Conversely, Jiangsu's notable improvement aligns with its industrial chain strengthening strategy, emphasizing green and intelligent manufacturing upgrades, clean energy substitution, and enhanced industry-university-research collaboration. Its robust industrial foundation and proactive policy support have created a conducive environment for efficiency gains. Zhejiang's slight decline may be linked to the slow low-carbon transition of its numerous small and medium-sized private enterprises, coupled with suboptimal energy efficiency in the logistics sector. The province's decentralized industrial structure may have further limited economy-wide technological efficiency improvements. As a later-industrializing region, Anhui remains relatively dependent on traditional energy sources and high-carbon industries. Its limited capacity for new energy deployment and technology absorption, combined with constraints in talent availability and innovation resources, collectively explain its lower CEE performance.



	2012-2015	2015-2018	2018-2021
Shanghai	1,241	1,220	1,091
Jiangsu	0,972	0,907	1,285
Zhejiang	1,044	0,847	0,999
Anhui	1,061	0,781	0,971

Fig. 3. The process of carbon emission efficiency changes in one municipality and three provinces, 2012-2021.

In summary, the divergent efficiency trajectories across these provincial-level units reflect significant differences in developmental stages, industrial structure, energy composition, and innovation capacity. Jiangsu achieved substantial growth through active industrial and technological upgrading, whereas Shanghai exhibits signs of marginal constraints despite maintaining high baseline efficiency. Both Zhejiang and Anhui, however, require further structural adjustments and technological enhancements to overcome existing bottlenecks in their transition toward low-carbon development.

Typical Urban Evolution Characteristics

To further elucidate the mechanisms driving the evolution of CEE in the YRD region, this study selected Yangzhou, Huzhou, and Fuyang as representative cases for comparative analysis. Based on panel data from 2012 to 2021, their dynamic CEE pathways were examined (Table 2), revealing notably divergent trajectories:

Yangzhou demonstrated sustained improvement in CEE. Between 2012 and 2018, its TFP remained below the production frontier (TFP<1), with gains in technical efficiency (EFF) largely offsetting the constraining effects of sluggish technological progress (TEC). From 2018 to 2021, however, EFF stabilized at a high level (mean≈1.0), while TEC increased markedly, exhibiting a phase growth rate of approximately 20.5%. This shift elevated TFP above the efficiency frontier, indicating a successful transition from management-led optimization to technology-driven growth.

Huzhou exhibited a fluctuating recovery pattern in CEE. During 2012-2015, a high technical efficiency index (EFF = 1.172) sustained leading TFP. However, from 2015 to 2018, simultaneous declines in both EFF and technological change (TEC), by approximately 23.5% and 19.8%, respectively, resulted in a pronounced TFP decrease. The 2018-2021 period witnessed a synergistic rebound, with substantial growth in both indices driving TFP to 1.265. This trajectory suggests that, following the challenges of structural adjustment, the city has reestablished synergy between technological innovation and management effectiveness.

In contrast, Fuyang consistently maintained low CEE throughout the study period. Its TFP remained below 0.85, with neither EFF nor TEC showing sustained improvement. Instead, these indicators displayed alternating declines across phases: during 2012-2015, EFF was notably low (0.638) despite TEC above 1; from 2015 to 2018, TEC modestly grew while EFF declined again; and in 2018-2021, EFF stagnated at a low level (0.756) with no significant TEC recovery. This pattern reflects systemic constraints in the city's capacity for technology absorption and management efficiency, indicating a failure to establish synergistic mechanisms for enhancing both dimensions of carbon emission performance.

These case analyses demonstrate that enhancing CEE in the Yangtze River Delta depends not on isolated technological or managerial interventions, but on the synergistic development of both components. While Yangzhou and Huzhou achieved efficiency growth through differentiated yet complementary pathways, highlighting the importance of aligning policy responsiveness with technological adaptability, Fuyang's persistently low efficiency underscores the structural constraints impeding green transition in some cities, pointing to the need for targeted policy interventions and systemic capacity building.

Table 2. Changes in Technical Efficiency Index, Technological Change Index, and Total Factor Productivity for Carbon Emissions in Yangzhou, Huzhou, and Fuyang, 2012-2021.

Period	City	EFF	TEC	TFP
2012-2015	Yangzhou	1.029	0.807	0.830
	Huzhou	1.172	0.921	1.079
	Fuyang	0.638	1.030	0.657
2015-2018	Yangzhou	1.396	0.642	0.896
	Huzhou	0.897	0.739	0.663
	Fuyang	0.648	1.126	0.730
2015-2021	Yangzhou	0.993	1.205	1.196
	Huzhou	1.116	1.134	1.265
	Fuyang	0.756	1.105	0.836

Spatial Feature Analysis

Overall Spatial Distribution Characteristics of the YRD Region

Based on panel data from three periods (2012-2015, 2015-2018, and 2018-2021), this study applied the Natural Breaks method in ArcGIS 10.2 to classify the CEE of 41 prefecture-level cities in the YRD into four distinct categories. This classification reveals clear spatial differentiation and dynamic evolution of CEE across the region (Fig. 4). The results indicate that the spatial distribution of CEE is characterized by a combination of multicentric, axial, and zonal patterns.

High-efficiency cities (TFP≥1.05) are predominantly concentrated around major urban nodes such as Shanghai, Nanjing, Hangzhou, and Hefei, demonstrating notable radiating and spillover effects. Ningbo, as a key port city, consistently ranks among the top tier in CEE, highlighting the potential advantages of open economies and transport hubs in advancing low-carbon development.

Higher-efficiency cities (TFP: 1.00-1.05) are mainly distributed along the Yangtze River mainstream and the Shanghai–Nanjing–Hangzhou development axis, forming a transitional efficiency belt that connects core urban centers. Within this category, Suzhou and Wuxi stand out due to their robust industrial foundations.

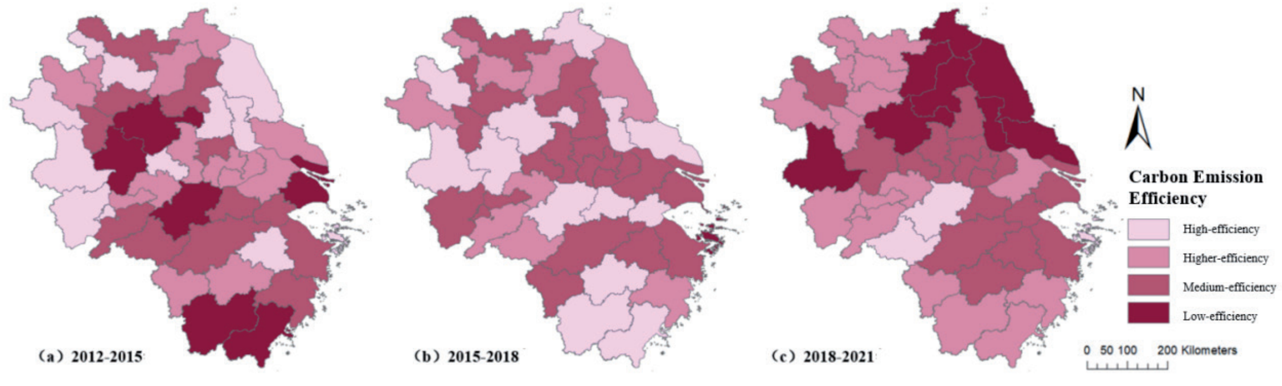


Fig. 4. Spatial distribution of carbon emission efficiency in the Yangtze River Delta Region from 2012-2021.

Medium-efficiency cities (TFP: 0.90-1.00) exhibit a zonal spatial distribution, concentrated in central Jiangsu and the coastal southeastern areas of Zhejiang. Their efficiency values fluctuated considerably during the study period, reflecting uncertainties associated with transitional development phases.

Low-efficiency cities (TFP<0.90) are primarily located in non-Yangtze River areas of Anhui Province, displaying distinct peripheral agglomeration characteristics. Over time, the number of cities in this category has declined, suggesting that regional policies, technology diffusion, and market mechanisms may have contributed to gradual efficiency improvements.

From a mechanism perspective, and considering both regional development realities and existing research, the spatial variation in CEE across the YRD can be attributed to the following factors: (1) industrial relocation and structural upgrading, wherein core cities have transferred energy-intensive industries to peripheral areas while focusing on high-end services, reinforcing a core–periphery efficiency divide; (2) geographic location and resource endowments, with cities along the Yangtze River benefiting from superior water transport and energy infrastructure, leading to lower energy costs and higher efficiency, in contrast to northern Anhui, which remains constrained by its geographical limitations and reliance on traditional energy sources; (3) spatial decay of technological spillovers, whereby the diffusion of innovation from high-efficiency regions diminishes with distance, limiting efficiency gains in peripheral areas; and (4) agglomeration economies, where high population and economic density facilitate green technological innovation and efficiency improvements through scale effects.

In summary, the evolving spatial patterns of CEE reveal pronounced regional disparities within the YRD and provide empirical spatial evidence to support the further optimization of regionally coordinated emission-reduction policies.

Spatial variation in CEE is also jointly influenced by government governance and resource resilience. Governments guide the relocation of high-carbon industries and the diffusion of green technologies through industrial policies and environmental regulations [38], forming high-high clusters. Regions with stronger resource utilization resilience [40, 41] demonstrate greater resilience to external shocks and sustain efficient emission patterns. Conversely, resource-dependent cities are prone to low-low lock-in during energy price fluctuations or policy adjustments, highlighting how insufficient regional resilience constrains low-carbon transition [42].

Evolutionary Characteristics of Cities at Different Hierarchical Levels

Based on 2021 permanent resident population data for districts within prefecture-level cities, this study categorizes the 41 cities in the Yangtze River Delta into five tiers: megacities, super-large cities, large cities, medium-sized cities, and small cities.From 2012 to 2021, their average CEE measured by TFP was 1.184, 1.104, 1.004, 0.942, and 0.976, respectively, showing a general inverse relationship with city size (Fig. 5).

Except for small cities, CEE improved across all city tiers during the study period. In terms of growth rates, large and medium-sized cities exhibited the most marked gains, with TFP increasing by 18.8% and 19.5%, respectively. Super-large cities recorded a 10.9% rise, while megacities and small cities experienced declines of 8.6% and 28.3%, respectively. These findings indicate that super-large, large, and medium-sized cities achieved notable improvements in CEE. Although megacities maintained the highest absolute efficiency levels, their growth momentum weakened, and small cities faced substantial constraints in enhancing performance.

The variations in CEE across city tiers can be attributed to multiple underlying factors. Super-large, large, and medium-sized cities generally exhibit stronger industrial adaptability and policy implementation capacity, enabling more effective efficiency gains through circular transformation of industrial parks, technological upgrades, and energy structure optimization. While megacities benefit from comprehensive monitoring systems and advanced technological capabilities, they also face greater systemic transition pressures and stronger path dependence, which complicates marginal improvements. In contrast, small cities are often constrained by limited resource accessibility, inadequate technological reserves, and fragmented policy coverage, resulting in a delayed and less effective green transition.

In summary, although city scale influences CEE, its effect is not linear. Urban centers of different sizes continue to encounter distinct challenges and divergent development pathways in their transition toward green and low-carbon futures.

Spatial Correlation Analysis

Global Spatial Autocorrelation Measurement Results

This study employs the global Moran's I index to examine the spatial autocorrelation of CEE in the YRD region from 2012 to 2021. As summarized in Table 3, the computed Moran's I values were consistently positive and statistically significant across all study periods (2012-2015: I = 0.715; 2015-2018: I = 0.867; 2018-2021: I = 0.734). All measurements passed the significance test at the 1% level ($p<0.01$), with Z-scores substantially exceeding critical thresholds, for instance, Z = 53.90 during 2012-2015. These results demonstrate strong and persistent positive spatial autocorrelation in CEE throughout the region. Specifically, the analysis reveals a clear spatial clustering pattern: cities with high CEE tend to agglomerate, as do those with low CEE. This non-random distribution aligns with broader trends in regional economic integration, industrial connectivity, and technology diffusion, underscoring the role of distinct spatial interdependence mechanisms in shaping the geography of CEE.

Local Spatial Autocorrelation Agglomeration Characteristics

To further examine the spatial dependence and local clustering patterns of CEE in the YRD region, this study employed Local Indicators of Spatial Association (LISA) to analyze three sub-periods: 2012-2015, 2015-2018, and 2018-2021 (Fig. 6). The results reveal a clear phased evolution in the spatial clustering structure of CEE, reflecting the ongoing transformation of regional development patterns under advancing integration.

During 2012-2015, high-high agglomerations appeared in a fragmented spatial pattern, primarily distributed in southeastern coastal Zhejiang and eastern Anhui. These regions were still expanding traditional manufacturing sectors, with industrial upgrading yet to be fully realized. The relatively scattered distribution of enterprises contributed to weak spatial continuity among high-efficiency units. While Shanghai and Ningbo emerged as prominent high-high clustering cores, they exhibited high-low or low-high heterogeneous patterns with neighboring cities such as Suzhou and Ma'anshan. This spatial heterogeneity reflects substantial disparities in industrial structure and efficiency levels between core cities and their peripheries, a pattern likely influenced by Shanghai's accelerated industrial transition occurring alongside intermediate industrialization stages in surrounding areas, under a still-developing regional coordination mechanism.

During 2015-2018, spatial polarization of CEE intensified. Shanghai and its surrounding areas sustained high-high clustering, maintaining elevated efficiency levels through enhanced technological innovation and service-oriented industrial restructuring. Concurrently, contiguous low-low agglomeration zones emerged in southwestern Zhejiang and central Anhui, further accentuating regional disparities. This divergence may be attributed to differentiated environmental regulation intensities. In southwestern Zhejiang, the phasing out of backward production capacity under stringent ecological policies contributed to localized efficiency depression. Meanwhile, regions such as Anhui received transfers of high-carbon industries from core areas, resulting in a carbon leakage effect that suppressed local CEE improvement.

During 2018-2021, as regional integration deepened, the spatial structure evolved toward a multi-centered, networked pattern of collaborative development. Continuous high-high agglomeration belts formed along the Yangtze River in Jiangsu, the coastal zone in Zhejiang, and eastern Anhui, indicating that cross-regional technology spillovers, industrial coordination, and green transition policies had begun to yield synergistic effects. While Shanghai and Ningbo maintained their leading positions, the efficiency gap with surrounding areas narrowed noticeably. Eastern Anhui progressively integrated into the high-efficiency zone by undertaking green industries and promoting new energy and materials sectors. This spatial restructuring reflects a transition in the regional development approach, from earlier gradient-based industrial transfer toward deeper, more collaborative integration.

Table 3. Global Moran's I for carbon emission efficiency in the Yangtze River Delta Region, 2012-2021.

Period	Moran's I	Expected Index	Variance	z	P-value
2012-2015	0.714987	-0.00171	0.000177	53.903685	0
2015-2018	0.86734	-0.00171	0.000177	65.316253	0
2018-2021	0.733987	-0.00171	0.000177	55.30311	0

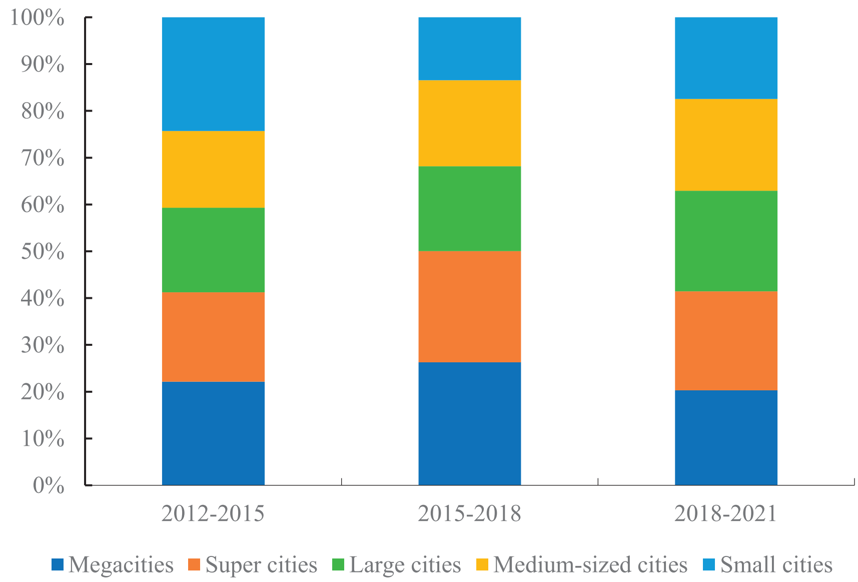


Fig. 5. Scale and structural characteristics of carbon emission efficiency in the YRD region, 2012-2021.

Discussion

The empirical results highlight the need for differentiated and coordinated policy strategies to enhance CEE across the YRD. Based on these findings, this study proposes the following policy recommendations to support green, low-carbon, and high-quality development in the YRD region:

(1) Promote Green Industrial Transformation and establish a Regional Collaborative Emission Reduction mechanism. We recommend the formulation of unified industrial carbon emission standards and a clean production assessment system applicable across the YRD. Building on the policy framework of the Ecological Green Integrated Development Demonstration Zone, cross-provincial joint supervision should be prioritized in key sectors such as steel and chemicals. Differentiated electricity pricing and tax incentives based on carbon emission intensity could be implemented, supplemented by a regional green manufacturing development fund to support corporate energy-saving upgrades and low-carbon transitions. Additionally, an enterprise environmental credit evaluation system and a cross-regional accountability mechanism should be established, supported by enhanced environmental information disclosure and public oversight.

(2) Facilitate integrated development of High-End, Low-Carbon service industries. A region-wide certification system for green service industries and low-carbon service standards should be established. High value-added sectors – such as finance, logistics, and data centers – should be encouraged to conduct regular carbon accounting and public disclosure. Core cities, including Shanghai and Hangzhou, are well-positioned to lead the development of low-carbon service industry clusters. Policy packages combining talent recruitment, R&D support, and market promotion should be deployed to accelerate the integration of digitalization and green transformation within the service sector. It is also advisable to incorporate service industry carbon efficiency indicators into local government

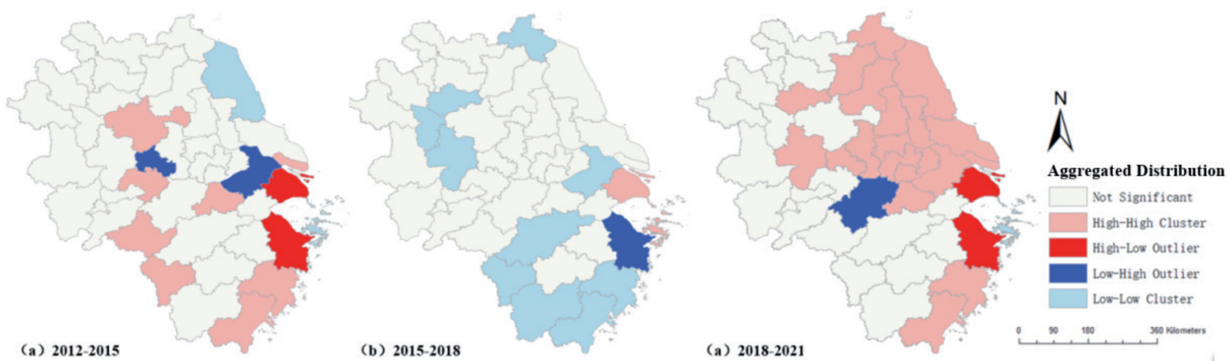


Fig. 6. Aggregated distribution of carbon emission efficiency in the Yangtze River Delta Region, 2012-2021.

performance appraisal systems, thereby guiding the transition of the service economy from scale expansion to quality-driven growth.

(3) Strengthen Low-Carbon Technology Innovation and Regional Collaborative Innovation networks. We propose the establishment of a special YRD joint research program on low-carbon technologies, along with shared regional platforms and key laboratories for green technology R&D, focusing on renewable energy, energy storage, and carbon capture, utilization, and storage (CCUS). A mechanism for sharing scientific and technological resources and mutual recognition of intellectual property rights across Shanghai, Jiangsu, Zhejiang, and Anhui should be established, accompanied by a joint fund to support the commercialization of low-carbon technologies, particularly demonstration and application projects in small and medium-sized enterprises. Initiatives such as hosting green technology fairs and establishing cross-regional carbon neutrality innovation demonstration zones will help enhance the region's overall innovation capacity and international influence in the green technology sector.

(4) Deepen regional coordination and policy integration. Building on the experience of the YRD Ecological and Green Integrated Development Demonstration Zone, a cross-administrative carbon emission control coordination mechanism should be established. This includes developing a unified regional carbon emission statistical monitoring platform, implementing joint carbon footprint accounting, and harmonizing environmental impact assessment standards. Efforts should be made to facilitate the cross-regional flow of energy, technology, and data resources. The establishment of a regional carbon inclusion mechanism and a green finance consortium should be explored to provide institutional support for achieving the "dual carbon" goals.

Conclusions

This study examines the spatiotemporal evolution and spatial aggregation patterns of CEE in the YRD region from 2012 to 2021, employing an integrated methodology that combines the super-efficiency SBM-DEA model, Malmquist index, and spatial autocorrelation analysis. Relative to existing literature, this research makes two principal contributions: first, it identifies the policy- and technology-driven mechanisms underlying the observed V-shaped fluctuation trend from a dynamic efficiency perspective; second, through spatial autocorrelation analysis, it reveals the transition of regional coordination from a core-periphery structure toward a multi-center network pattern, thereby enriching the understanding of CEE dynamics within regional integration contexts. Methodologically, the incorporation of nighttime light data into a total-factor efficiency framework that accounts for undesirable outputs enables a high-resolution dynamic assessment of CEE, demonstrating a novel analytical approach. The principal findings are summarized as follows:

Temporal Evolution: Regional CEE demonstrated a fluctuating upward trend characterized by a V-shaped trajectory, delineated into three distinct phases: a Policy-Driven Phase (2012-2015), during which efficiency remained elevated due to administrative measures and emission reduction policies; a Transition and Adjustment Phase (2015-2018), marked by efficiency decline amid structural friction during industrial transformation and high-carbon industry transfer; and an Innovation-Driven Phase (2018-2021), in which efficiency rebounded significantly, propelled by technological advances and energy structure optimization.

Spatial Pattern: CEE exhibits a multi-nodal and spatially graded structure. High-efficiency zones are concentrated in core cities (Shanghai, Nanjing, Hangzhou, Hefei, and Ningbo), while medium- and low-efficiency cities are mainly distributed across peripheral regions such as northern and western Anhui, forming a distinct core-periphery hierarchy.

Regional and Hierarchical Disparities: At the provincial level, Shanghai sustained the highest CEE, albeit with a modest declining trend, whereas Jiangsu exhibited the most pronounced growth. Zhejiang and Anhui both showed V-shaped fluctuations yet remained at relatively low efficiency levels overall. Across city tiers, super-large, large, and medium-sized cities achieved notable efficiency gains. By contrast, megacities experienced slowing growth momentum, and small cities continued to face substantial developmental constraints.

Spatial Autocorrelation: A consistently significant positive spatial autocorrelation in CEE was identified throughout the study period. The spatial clustering pattern evolved through three clear stages: from an initially fragmented distribution, through a phase of polarized adjustment, toward an increasingly multi-centered, contiguous, and collaborative agglomeration structure, reflecting the strengthening effect of regional integration on CEE.

Additionally, this study opens avenues for theoretical refinement within regional sustainability transitions. The observed V-shaped efficiency trajectory and the spatial shift from a core-periphery to a multi-center network structure resonate strongly with evolutionary economic geography and multi-level perspective (MLP) frameworks. These findings empirically underscore how exogenous policy pressures and endogenous technological niche-innovations interact to reconfigure regional socio-technical regimes. Future research could further dissect this co-evolution by integrating institutional and technological proximity into spatial econometric models. Such an approach would elucidate the nuanced mechanisms through which regional integration either reinforces or mitigates spatial carbon lock-in, thereby advancing a more dynamic theory of low-carbon transitions under multi-scalar governance. This study has several limitations. First, while it identifies key spatiotemporal patterns of CEE, the analysis of underlying driving mechanisms remains incomplete. The respective roles of economic structure, environmental regulation, and energy consumption in shaping spatial heterogeneity have not been systematically examined. Second, the research does not incorporate micro-level analysis of carbon emission behaviors (e.g., at the enterprise level), as macro-level statistical data are insufficient to capture the full heterogeneity of transition pathways. Future research should combine enterprise-level surveys with macro-scale policy evaluation, adopting approaches such as mechanism design and multi-scenario simulation. The findings of this study hold significant reference value for developing regions undergoing rapid industrialization and urbanization. For instance, areas such as Southeast Asia (e.g., Vietnam, Indonesia) and South America (e.g., Brazil, Peru) similarly face the challenge of decoupling economic growth from carbon emissions. The YRD region's experience in enhancing CEE through regional integration for coordinated emission reduction, green industrial transformation, and collaborative low-carbon technology networks offers the following insights for these regions: 1) Establish cross-administrative carbon emission monitoring and collaborative management platforms to prevent carbon leakage and policy fragmentation; 2) Promote the parallel transfer of high-carbon industries and green upgrading, developing resilient low-carbon economies based on local resource endowments; 3) Strengthen government-enterprise-research collaboration to build green technology diffusion mechanisms suitable for developing regions. 4) Future research should explore cross-national comparisons to uncover common and distinct mechanisms of CEE across different institutional and cultural contexts.

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Conflict of Interest

The authors declare no conflict of interest.

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