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EDITED BY
Francesco Bianco,
University of Cassino, Italy

REVIEWED BY
Gennaro Trancone,
University of Naples Federico II, Italy
Yanzhi Jin,
Xi'an University of Technology, China

*CORRESPONDENCE
Ping Jiang,
✉ jiangping@fudan.edu.cn

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# Carbon emission efficiency system of wastewater treatment in China's Yangtze river economic belt: spatial-temporal evolution and influencing factors

Xu Chu[1,2], Ping Jiang[2,3]*, Xinling Jiang[1,2] and Haoxuan Cheng[4]

[1]School of Environment, Fudan University, Shanghai, China, [2]Fudan Tyndall Center, Fudan University, Shanghai, China, [3]Institute for Global Public Policy, Fudan University, Shanghai, China, [4]School of International and Public Affairs, Shanghai Jiao Tong University, Shanghai, China

**Introduction:** Improving the carbon emission efficiency of wastewater treatment (CEEWT) is essential for achieving the coordinated goals of pollution reduction and carbon mitigation. As a key economic and ecological region in China, the Yangtze River Economic Belt (YEB) provides an important context for examining the low-carbon performance of regional wastewater treatment systems. However, existing studies mainly focus on plant-level efficiency or single environmental indicators, with limited attention to regional-scale efficiency and its spatiotemporal evolution.
**Methods:** Based on the IPCC carbon accounting framework and an entropy weight–TOPSIS method, this study evaluates the CEEWT across provinces in the YEB from 2011 to 2020. The spatiotemporal evolution and regional disparities are systematically analyzed, and the underlying mechanisms are discussed from economic, technological, and institutional perspectives.
**Results:** The results indicate that CEEWT in the YEB shows an overall upward but fluctuating trend, while significant and persistent regional disparities remain. Downstream provinces such as Jiangsu, Shanghai, and Zhejiang consistently exhibit higher efficiency levels, whereas many midstream and upstream provinces lag behind. No clear convergence pattern is observed, suggesting strong path dependence shaped by long-term structural conditions.
**Discussion/Conclusion:** These findings highlight the necessity of differentiated, region-specific policy approaches to promote the low-carbon transition of wastewater treatment systems. This study provides a scientific basis for optimizing regional pollution and carbon reduction strategies in large-scale economic belts.

KEYWORDS

**carbon emission efficiency, regions, TOPSIS method, wastewater, Yangtze river economic belt**

## 1 Introduction

With the increasing severity of global climate change, greenhouse gas mitigation has become a central issue in achieving sustainable development worldwide. In this context, the wastewater treatment sector, as a critical component of urban infrastructure systems, has attracted growing attention from both academia and policymakers due to its substantial energy consumption and carbon emissions. Existing studies indicate that wastewater treatment systems play an indispensable role in safeguarding water environmental quality and improving public health; however, the large amounts of electricity and chemical inputs consumed during their operation also make them a significant source of urban carbon emissions (Corominas et al., 2012; Mo and Zhang, 2013). Consequently, reducing carbon emissions from wastewater treatment processes while maintaining pollution abatement performance has become a key challenge for coordinating low-carbon transition and water environmental governance in cities.

As one of the largest wastewater treatment markets in the world, China has achieved remarkable progress in the construction of wastewater treatment facilities and the expansion of treatment capacity in recent decades. In particular, in the Yangtze River Economic Belt (YREB), rapid urbanization and industrialization have driven a continuous increase in the number and scale of wastewater treatment plants (Ministry of Housing and Urban-Rural Development of China MOHURD, 2011). Nevertheless, existing studies have pointed out that wastewater treatment systems in this region still face multiple challenges in terms of operational efficiency, energy consumption, and carbon emission control, including relatively low operational efficiency in some areas, suboptimal energy use structures, and pronounced regional disparities (Liu et al., 2019; Zhang et al., 2020). These issues have, to some extent, constrained the green transformation of the wastewater treatment sector under China's "dual-carbon" targets.

From a research perspective, the existing literature has mainly evaluated wastewater treatment systems from the perspectives of technical efficiency, energy efficiency, or environmental performance, using methods such as data envelopment analysis (DEA), life cycle assessment (LCA), and material flow analysis (MFA) (Molinos-Senante et al., 2014; Corominas et al., 2013; Zhao et al., 2015). While these studies provide valuable insights into the operational characteristics and environmental impacts of wastewater treatment systems, two limitations remain evident. First, efficiency-related concepts are often defined inconsistently, and carbon emissions are frequently treated as secondary outcomes rather than core evaluation objectives. Second, most studies focus on individual wastewater treatment plants or single cities, whereas systematic comparisons of carbon emission efficiency at the river-basin or regional scale remain relatively scarce (Zhou et al., 2008; Chen et al., 2017).

Against this background, it is necessary to adopt a regional perspective to comprehensively assess the performance of wastewater treatment systems under the dual constraints of pollution reduction and carbon mitigation. Spanning eastern, central, and western China, the YREB exhibits significant heterogeneity in economic development levels, industrial structures, and infrastructure conditions, making it an ideal case for investigating regional disparities and spatial dynamics in wastewater treatment carbon emission efficiency. A systematic analysis of carbon emission efficiency in this region can not only deepen the understanding of low-carbon transition pathways in regional water systems, but also provide scientific support for formulating differentiated wastewater treatment and emission reduction policies.

Accordingly, this study clearly defines the concept of carbon emission efficiency of wastewater treatment (CEEWT) and constructs a multi-indicator comprehensive evaluation framework to examine the spatiotemporal evolution and driving factors of wastewater treatment carbon emission efficiency in the YREB. The potential contributions of this study are threefold. First, it conceptually distinguishes CEEWT from conventional energy efficiency and environmental performance measures, thereby enriching the theoretical understanding of efficiency assessment in the wastewater sector. Second, it extends existing research by evaluating wastewater treatment carbon emission efficiency at the regional scale. Third, it empirically reveals the evolution patterns and driving mechanisms of CEEWT in the YREB, providing policy-relevant insights for the coordinated advancement of water environmental governance and low-carbon development.

## 2 Literature review

### 2.1 Conceptual definition and theoretical background of CEEWT

In the existing literature, efficiency-related concepts commonly applied in the wastewater treatment sector include energy efficiency, environmental performance, eco-efficiency, and carbon efficiency. However, these concepts differ substantially in terms of research focus, input–output boundaries, and policy implications (Kuosmanen and Kortelainen, 2005; Zaim and Taskin, 2000; Zhang et al., 2014). The concept of CEEWT proposed in this study is not a simple rebranding of these existing measures, but rather a context-specific and integrated efficiency indicator.

From the perspective of environmental economics, CEEWT emphasizes the minimization of carbon emissions directly or indirectly associated with wastewater treatment processes while delivering pollution abatement services under given economic and institutional constraints. Its essence lies in resource allocation efficiency in the presence of internalized environmental externalities (Pigou, 1920). From the standpoint of efficiency analysis theory, CEEWT represents a typical multi-input–multi-output efficiency problem, incorporating conventional inputs such as capital, energy, and labor, desired outputs such as treatment capacity and pollutant removal, and carbon emissions explicitly treated as undesirable outputs (Färe et al., 1989; Chung et al., 1997).

Within the framework of urban metabolism and sustainable development theory, wastewater treatment systems constitute a critical node in urban material and energy flows. Their operational performance affects not only water environmental quality but also urban low-carbon transition through energy consumption and greenhouse gas emissions (Kennedy et al., 2011; Zhang et al., 2015). Therefore, CEEWT highlights a comprehensive evaluation of wastewater treatment system performance under the dual objectives of pollution reduction and carbon mitigation, distinguishing it from indicators that focus solely on unit energy consumption or single pollution control outcomes.

### 2.2 Empirical studies on wastewater treatment efficiency and carbon performance

Empirical research on efficiency in the water and wastewater sector generally falls into three categories: studies on operational or technical efficiency, environmental or eco-efficiency, and carbon emission or energy–environment efficiency.

Regarding operational and technical efficiency, a large body of studies has employed DEA and SBM-DEA models to assess the efficiency of municipal wastewater treatment plants under different scales and treatment technologies. These studies consistently find that scale effects, process configurations, and management practices are key determinants of efficiency (Molinos-Senante et al., 2016; Athanassopoulos, 2000). However, most of these analyses focus on treatment capacity, operating costs, or energy consumption, with carbon emissions rarely incorporated explicitly into the evaluation framework.

In studies on environmental and eco-efficiency, researchers have progressively incorporated pollutant removal as desired outputs and pollution loads or excessive discharges as undesirable outputs to assess the environmental performance of wastewater treatment systems under regulatory constraints (Yang et al., 2018; Hu and Wang, 2006). While these approaches provide useful tools for characterizing pollution reduction performance, carbon emissions are often treated as ancillary variables rather than central evaluation targets.

More recently, driven by growing concerns over climate change, some studies have examined the carbon emission characteristics and efficiency of wastewater treatment systems. These studies typically adopt LCA or MFA to quantify carbon footprints of different treatment technologies, or integrate carbon emissions as undesirable outputs within DEA-based frameworks (Gu et al., 2017; Longo et al., 2016). Although these contributions offer important insights into emission sources and mitigation potential at the process or plant level, systematic assessments of wastewater treatment carbon emission efficiency at the regional or river-basin scale remain limited.

### 2.3 Theoretical mechanisms influencing wastewater treatment efficiency and carbon performance

At the theoretical level, wastewater treatment efficiency and carbon performance are jointly influenced by institutional, technological, and economic factors. According to the Porter Hypothesis, well-designed environmental regulations may stimulate technological innovation and managerial improvements, thereby enhancing resource-use efficiency and environmental performance (Porter and van der Linde, 1995). In the wastewater sector, stricter discharge standards and energy or carbon constraints may incentivize process upgrading and operational optimization, ultimately improving CEEWT (Ambec et al., 2013).

The Environmental Kuznets Curve (EKC) hypothesis provides another important lens for understanding the relationship between economic development and environmental performance (Grossman and Krueger, 1995). Some studies suggest that in the context of water environmental governance, increased economic development is associated with higher investment in wastewater treatment infrastructure and technological advancement, potentially leading to phased improvements in environmental performance. However, this relationship exhibits substantial heterogeneity across regions and environmental indicators, and its applicability to wastewater treatment carbon emission efficiency remains to be empirically verified (Dinda, 2004).

In addition, technological conditions, fiscal investment, pricing and cost-recovery mechanisms, energy prices, and regional governance arrangements have all been identified as important drivers of wastewater treatment efficiency and carbon performance (OECD, 2010; IPCC, 2019). Nevertheless, existing studies often examine these factors in isolation, and comprehensive analyses integrating multiple drivers within a unified analytical framework remain relatively scarce.

### 2.4 Research gaps and positioning of this study

In summary, although the literature on wastewater treatment efficiency and carbon emissions has expanded rapidly, several gaps remain. First, at the conceptual level, the distinction between carbon emission efficiency and related concepts such as energy efficiency and environmental efficiency has not been sufficiently clarified. Second, in terms of spatial scale, systematic comparisons of wastewater treatment carbon emission efficiency at the regional or river-basin level are still limited. Third, variations in indicator systems and methodological choices across studies hinder the comparability of existing findings (Wang and Su, 2019; Wang et al., 2021).

To address these gaps, this study focuses on the YREB and, based on a clear conceptualization of CEEWT, develops a multi-indicator comprehensive evaluation framework to analyze the spatiotemporal dynamics and driving factors of regional wastewater treatment carbon emission efficiency. By doing so, this study aims to provide new empirical evidence and policy-relevant insights that complement and extend the existing literature.

## 3 Research data and methods

### 3.1 Data and variables

The data used in this study were obtained from authoritative public sources, including the China Urban and Rural Construction Statistical Yearbook and the China Statistical Yearbook. These datasets ensure data consistency, inter regional comparability, and long-term temporal continuity, which are essential for a spatiotemporal efficiency analysis covering multiple provinces over an extended period.

#### 3.1.1 Conceptual logic of indicator selection

CEEWT reflects the ability of a region to achieve higher levels of socioeconomic output and public service provision with lower carbon emissions generated during wastewater treatment processes. From a systems perspective, wastewater treatment activities are embedded within broader urban economic, demographic, and governance structures. Therefore, CEEWT is not solely determined by plant-level technologies but is jointly shaped by economic scale, population pressure, fiscal capacity, and government intervention.

TABLE 1 Variable description.

| Dimension | Indicator | Definition | Interpretation/Mechanism | Direction |
|---|---|---|---|---|
| Population | Resident population | Total permanent population at year-end | Proxy for service demand and scale effects in wastewater treatment systems | + |
| Capital input | Environmental protection expenditure | Government expenditure on environmental protection | Indicator of capital investment in wastewater treatment infrastructure and technological upgrading | + |
| Government intervention | Government R&D expenditure | Fiscal expenditure on research and development | Proxy for governmental support for technological innovation in wastewater treatment | + |
| Government intervention | Government expenditure/GDP | Ratio of government expenditure to GDP | Indicator of governance intensity and institutional capacity | + |
| Economic development | GDP | Gross domestic product | Proxy for economic development level and fiscal capacity | + |
| Economic structure | Proportion of tertiary industry | Share of tertiary industry in GDP | Indicator of industrial structure upgrading and cleaner production orientation | + |
| Urbanization | Urban population ratio | Proportion of urban population | Proxy for urbanization level and centralized wastewater treatment capacity | + |
| Economic openness | Total imports and exports | Total value of imports and exports | Indicator of economic openness and potential technology spillovers | + |
| Environmental cost | Carbon emissions from wastewater treatment | Estimated $CO_2$ emissions from wastewater treatment processes | Undesirable output representing the environmental cost of wastewater treatment | − |

All indicators are constructed at the regional level to evaluate system-level carbon emission efficiency of wastewater treatment rather than plant-level technical efficiency.

Following this logic, the indicator system in this study is constructed based on three principles: scientific relevance, data availability, and cross-regional comparability. The evaluation framework includes one negative indicator (carbon emissions from wastewater treatment) and multiple positive indicators grouped into four dimensions: labor, capital, government intervention, and economic development (Table 1).

### 3.1.2 Negative indicator: carbon emissions from wastewater treatment

Carbon emissions from wastewater treatment are treated as the sole negative indicator, as they directly represent the environmental cost of wastewater management activities. Higher emissions indicate greater energy consumption, chemical use, and process-related greenhouse gas releases, thereby reducing carbon emission efficiency. This treatment is consistent with existing efficiency and environmental performance studies, where undesirable outputs are explicitly modeled as negative indicators.

### 3.1.3 Positive indicators and mechanism explanations

#### 3.1.3.1 Labor: total resident population

Total resident population is used as a proxy variable for labor input and service demand in the wastewater treatment system. Although population size does not directly measure technical staff or managerial capacity within wastewater treatment plants, it reflects two critical mechanisms:

Scale effect: Larger populations generate higher wastewater volumes, which may enable economies of scale in wastewater treatment infrastructure and operation.

Labor and demand pressure: Population size is closely associated with labor availability, urban service demand, and fiscal allocation priorities, indirectly influencing the organization and efficiency of wastewater treatment systems.

This proxy has been widely adopted in macro-level environmental efficiency studies due to the lack of consistent cross-regional data on sector-specific human capital.

#### 3.1.3.2 Capital: urban environmental protection expenditure

Urban environmental protection expenditure represents capital investment dedicated to environmental infrastructure, including wastewater treatment facilities, pipeline networks, and pollution control equipment. Higher investment levels generally indicate improved treatment capacity, upgraded equipment, and enhanced operational stability, which collectively contribute to reducing unit carbon emissions from wastewater treatment.

This indicator captures the financial foundation supporting wastewater treatment systems and reflects a region's long-term commitment to environmental governance.

#### 3.1.3.3 Government intervention

Government intervention is measured using two indicators: government R&D expenditure and government spending as a percentage of GDP.

Government R&D expenditure reflects the intensity of public investment in technological innovation, including energy-saving processes, treatment optimization, and low-carbon technologies relevant to wastewater management.

Government spending as a percentage of GDP captures the overall strength of government involvement in public affairs and environmental regulation, representing top-down institutional capacity rather than specific project-level inputs.

Together, these indicators characterize both technological guidance and institutional enforcement, which are key drivers of efficiency improvement under environmental regulation frameworks.

#### 3.1.3.4 Level of economic development

The level of economic development is represented by four indicators: GDP, percentage of urban population, value added of the tertiary industry, and import and export value. These variables describe different structural dimensions of economic development rather than serving as direct drivers of carbon emissions.

GDP reflects overall economic scale and fiscal capacity to support environmental infrastructure.

Percentage of urban population captures urbanization level, which is closely related to centralized wastewater treatment coverage and infrastructure efficiency.

Value added of the tertiary industry reflects industrial structure upgrading, as service-oriented economies typically generate lower pollution intensity compared to manufacturing-dominated structures.

Import and export value indicates economic openness and integration into global markets, which often promotes cleaner production standards, technological diffusion, and environmental regulation convergence.

Although economic growth and population expansion may increase wastewater generation, their inclusion as positive indicators does not imply that "more is always better." Instead, within the TOPSIS framework, these variables contribute to efficiency evaluation by jointly considering outputs and environmental costs, avoiding simplistic one-dimensional interpretations.

### 3.1.4 Justification of positive–negative classification

Only carbon emissions from wastewater treatment are defined as a negative indicator because they constitute the undesirable output of the system. All other indicators are treated as positive inputs or contextual factors that support wastewater treatment capacity and governance.

Potential trade-offs between economic growth, population expansion, and environmental pressure are addressed implicitly through the efficiency framework, where higher emissions penalize performance even under high economic output. Therefore, this classification does not oversimplify the system but rather aligns with the theoretical definition of efficiency as the balance between desirable outputs and undesirable environmental impacts.

## 3.2 IPCC method for estimating carbon emissions from wastewater treatment

Carbon emissions from wastewater treatment were estimated following the Intergovernmental Panel on Climate Change (IPCC) Guidelines for National Greenhouse Gas Inventories. Given the regional and temporal scope of this study, which covers 11 provinces and municipalities in the YEB over a 10-year period, the IPCC Tier 1 methodology was adopted to ensure data consistency, transparency, and cross-regional comparability.

The IPCC approach allows carbon emissions associated with wastewater treatment to be decomposed into emissions from methane ($CH_4$) and nitrous oxide ($N_2O$) generated during wastewater and sludge treatment processes. The total carbon dioxide equivalent emissions from wastewater treatment are calculated as Equation 1:

$$EF_{WWTP} = \left(EF_{CH_4} + EF_{N_2O} + EF_{sludge}\right) \times GWP_{CH_4} \tag{1}$$

Where $EF_{WWTP}$ denotes total carbon emissions from wastewater treatment (t $CO_2$e), $EF_{CH_4}$ represents methane emissions from wastewater treatment, $EF_{N_2O}$ represents nitrous oxide emissions, and $EF_{sludge}$ denotes methane emissions from sludge landfill disposal.

Methane emissions from wastewater treatment are calculated as Equation 2:

$$EF_{CH_4} = TOW \times EF_{CH_4} \tag{2}$$

where $TOW$ is the total amount of degradable organic matter in wastewater, expressed as biochemical oxygen demand (BOD), and $EF_{CH_4}$ is the methane emission factor. Due to the lack of consistent provincial-level BOD monitoring data, the BOD/COD ratio recommended by the IPCC (0.43) was adopted to derive BOD values from COD statistics.

Nitrous oxide emissions are calculated as Equation 3:

$$EF_{N_2O} = NE \times EF_E \times \frac{44}{28} \tag{3}$$

where $NE$ is the nitrogen content in wastewater and $EF_E$ is the emission factor for $N_2O$.

Methane emissions from sludge landfill treatment are calculated as Equation 4:

$$EF_{sludge} = (ST \times L_0 - R) \times (1 - OX) \tag{4}$$

where $ST$ is the amount of sludge generated, $L_0$ is the methane generation potential, $R$ represents methane recovery, and $OX$ denotes the oxidation factor.

All emission factors and coefficients were taken from the IPCC Tier 1 default values to maintain methodological consistency across provinces. While these parameters do not explicitly capture spatial heterogeneity in wastewater composition, treatment technologies, or climatic conditions, they provide a conservative and standardized estimation framework suitable for comparative efficiency analysis at the regional scale. The limitations associated with this assumption are further discussed in the Conclusion section.

## 3.3 Entropy weight–TOPSIS method to measure CEEWT

### 3.3.1 Rationale for method selection

To evaluate the CEEWT across regions, this study employs a combined entropy weight–TOPSIS approach. This method was selected for three primary reasons.

First, unlike frontier-based methods such as Data Envelopment Analysis (DEA) or Stochastic Frontier Analysis (SFA), the entropy weight–TOPSIS method does not require assumptions regarding production frontiers or functional forms, making it more suitable

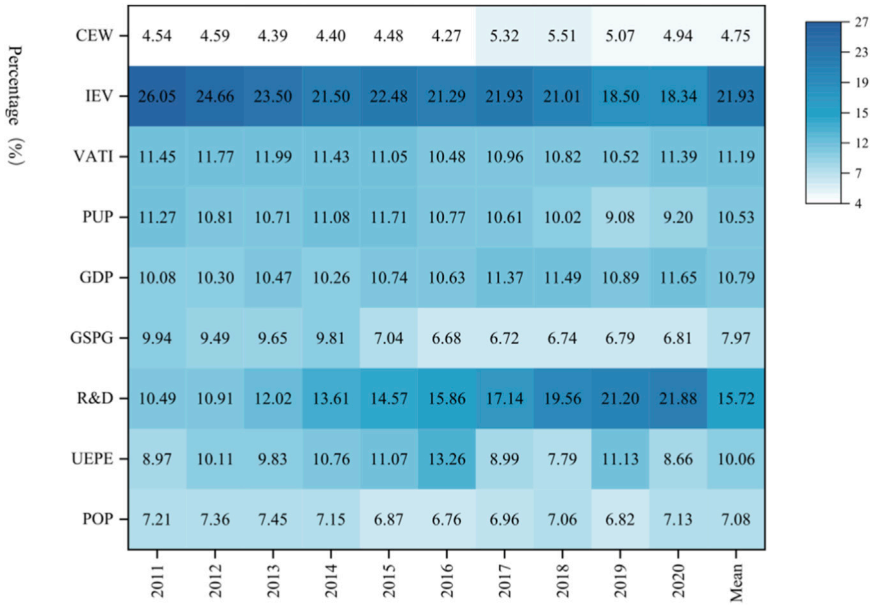


FIGURE 1
Weighting of evaluation indicators. CEW, Carbon emissions from wastewater; GSPG: Government spending as a percentage of GDP; IEV, Import and export value; R&D: Government R&D expenditures; VATI, Value added of tertiary industry; UEPE: Urban environmental protection expenditures; PUP, Percentage of urban population; POP: Population.

for composite efficiency evaluation involving heterogeneous regions with diverse economic and institutional backgrounds.

Second, the entropy weight method objectively determines indicator weights based on data variability, reducing subjectivity associated with expert judgment or pre-assigned weights. This is particularly important when multiple socioeconomic and governance-related indicators are involved.

Third, the TOPSIS method evaluates relative efficiency by measuring the distance of each region from an ideal solution and a worst solution, which aligns with the conceptual definition of CEEWT as a balance between desirable outputs and undesirable environmental impacts rather than a strict production efficiency measure.

### 3.3.2 Entropy weight method

The entropy weight method was used to determine the relative importance of each evaluation indicator. Let $x_{ij}$ denote the value of indicator $j$ for region $i$. The original data matrix is first normalized to eliminate scale differences.

For positive indicators, normalization is performed as:

$$z_{ij} = \frac{x_{ij} - \min\left(x_j\right)}{\max\left(x_j\right) - \min\left(x_j\right)} \tag{5}$$

For negative indicators, normalization is performed as:

$$z_{ij} = \frac{\max\left(x_j\right) - x_{ij}}{\max\left(x_j\right) - \min\left(x_j\right)} \tag{6}$$

The entropy value for each indicator is then calculated, followed by the computation of its degree of variation and corresponding weight. Indicators with greater variability across regions are assigned higher weights, reflecting their stronger discriminatory power in efficiency evaluation.

### 3.3.3 TOPSIS method

Based on the weighted normalized matrix, the positive ideal solution and negative ideal solution are determined. The Euclidean distance between each region and the two ideal solutions is then calculated. The relative closeness coefficient is computed as the final efficiency score, ranging from 0 to 1, with higher values indicating higher carbon emission efficiency of wastewater treatment.

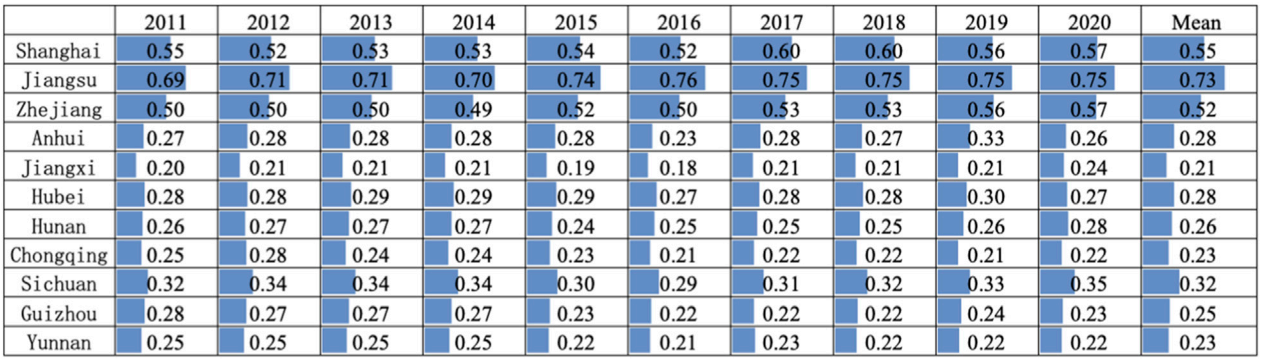
This approach allows for a comprehensive ranking of regions while avoiding the restrictive assumptions associated with Frontier efficiency models.

# 4 Results and discussion

## 4.1 Indicator weights and methodological clarification

Figure 1 reports the indicator weights derived from the entropy-weighting method. It should be emphasized at the outset that a higher entropy weight reflects greater information variability across provinces rather than a stronger causal impact on CEEWT. Accordingly, the weights are interpreted as indicators' relative contributions to differentiating regional efficiency performance, rather than as evidence of economic dominance or policy effectiveness.

Among all indicators, Import and Export Value (IEV) exhibits the highest average weight (approximately 22%), followed by Government R&D Expenditure (around 16%). This pattern indicates substantial cross-provincial heterogeneity in trade



| | 2011 | 2012 | 2013 | 2014 | 2015 | 2016 | 2017 | 2018 | 2019 | 2020 | Mean |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Shanghai | 0.55 | 0.52 | 0.53 | 0.53 | 0.54 | 0.52 | 0.60 | 0.60 | 0.56 | 0.57 | 0.55 |
| Jiangsu | 0.69 | 0.71 | 0.71 | 0.70 | 0.74 | 0.76 | 0.75 | 0.75 | 0.75 | 0.75 | 0.73 |
| Zhejiang | 0.50 | 0.50 | 0.50 | 0.49 | 0.52 | 0.50 | 0.53 | 0.53 | 0.56 | 0.57 | 0.52 |
| Anhui | 0.27 | 0.28 | 0.28 | 0.28 | 0.28 | 0.23 | 0.28 | 0.27 | 0.33 | 0.26 | 0.28 |
| Jiangxi | 0.20 | 0.21 | 0.21 | 0.21 | 0.19 | 0.18 | 0.21 | 0.21 | 0.21 | 0.24 | 0.21 |
| Hubei | 0.28 | 0.28 | 0.29 | 0.29 | 0.29 | 0.27 | 0.28 | 0.28 | 0.30 | 0.27 | 0.28 |
| Hunan | 0.26 | 0.27 | 0.27 | 0.27 | 0.24 | 0.25 | 0.25 | 0.25 | 0.26 | 0.28 | 0.26 |
| Chongqing | 0.25 | 0.28 | 0.24 | 0.24 | 0.23 | 0.21 | 0.22 | 0.22 | 0.21 | 0.22 | 0.23 |
| Sichuan | 0.32 | 0.34 | 0.34 | 0.34 | 0.30 | 0.29 | 0.31 | 0.32 | 0.33 | 0.35 | 0.32 |
| Guizhou | 0.28 | 0.27 | 0.27 | 0.27 | 0.23 | 0.22 | 0.22 | 0.22 | 0.24 | 0.23 | 0.25 |
| Yunnan | 0.25 | 0.25 | 0.25 | 0.25 | 0.22 | 0.21 | 0.23 | 0.22 | 0.22 | 0.22 | 0.23 |

FIGURE 2
The value of CEEWTYEB.

**TABLE 2** The ranking of CEEWTYEB.

| Province | 2011 | 2012 | 2013 | 2014 | 2015 | 2016 | 2017 | 2018 | 2019 | 2020 | Mean rank |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Jiangsu | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| Shanghai | 2 | 2 | 2 | 2 | 2 | 2 | 2 | 2 | 3 | 2 | 2 |
| Zhejiang | 3 | 3 | 3 | 3 | 3 | 3 | 3 | 3 | 2 | 3 | 3 |
| Sichuan | 4 | 4 | 4 | 4 | 4 | 4 | 4 | 4 | 4 | 4 | 4 |
| Hubei | 5 | 5 | 5 | 5 | 5 | 5 | 6 | 5 | 6 | 6 | 5 |
| Anhui | 7 | 6 | 6 | 6 | 6 | 7 | 5 | 6 | 5 | 7 | 6 |
| Hunan | 8 | 9 | 7 | 8 | 7 | 6 | 7 | 7 | 7 | 5 | 7 |
| Guizhou | 6 | 8 | 8 | 7 | 9 | 8 | 9 | 8 | 8 | 9 | 8 |
| Yunnan | 10 | 10 | 9 | 9 | 10 | 9 | 8 | 10 | 9 | 10 | 9 |
| Chongqing | 9 | 7 | 10 | 10 | 8 | 10 | 10 | 9 | 11 | 11 | 10 |
| Jiangxi | 11 | 11 | 11 | 11 | 11 | 11 | 11 | 11 | 10 | 8 | 11 |

openness and public innovation investment within the YEB. Coastal provinces such as Jiangsu and Shanghai exhibit significantly higher external trade exposure than inland provinces, while fiscal disparities across regions translate into markedly different levels of government-supported technological innovation.

Several indicators—including GDP, urbanization rate, value added of the tertiary industry, and urban environmental protection expenditure—display relatively similar weights (approximately 10%). This reflects the fact that most YEB provinces maintain relatively high levels of economic development and urbanization compared with the national average, resulting in moderate interregional dispersion rather than dominance by a single dimension.

To address potential concerns regarding indicator redundancy and multicollinearity, variance inflation factor (VIF) diagnostics and pairwise correlation analyses were conducted and are reported in Supplementary Appendix A. The results indicate that multicollinearity remains within acceptable thresholds, supporting the robustness of the entropy-based weighting scheme. In addition, principal component analysis (PCA)–based alternative weighting results are provided in Supplementary Appendix B, which yield highly consistent provincial rankings, further confirming the stability of the CEEWT measurement.

## 4.2 Spatiotemporal patterns of CEEWT in the YEB

Based on the entropy-weighted TOPSIS results, Figure 2 presents the temporal evolution of CEEWT across the YEB from 2011 to 2020. Overall, CEEWT exhibits a gradually improving trend with noticeable short-term fluctuations, particularly during the 2015–2017 period. Substantial heterogeneity persists across provinces, indicating uneven progress in achieving low-carbon wastewater treatment.

From a spatial perspective, provinces can be classified into three distinct echelons according to their long-term efficiency performance (Table 2). This stratification remains relatively stable over time, suggesting the presence of persistent structural factors shaping regional CEEWT.

## 4.3 Spatial differentiation and underlying mechanisms

### 4.3.1 First echelon: Jiangsu province

Jiangsu consistently ranks first in CEEWT throughout the study period, with an average efficiency score of 0.73. This sustained leadership reflects a synergistic interaction between economic scale, technological capacity, and industrial upgrading.

First, Jiangsu's strong economic base provides fiscal capacity for continuous investment in wastewater treatment infrastructure and low-carbon technologies. Second, its exceptionally high government R&D expenditure enhances technological learning, process optimization, and energy efficiency within wastewater treatment systems. Third, the province's advanced tertiary industry structure reduces dependence on carbon-intensive production, indirectly lowering the emissions burden per unit of treated wastewater.

From a theoretical perspective, Jiangsu's performance is consistent with induced technological innovation theory, whereby stricter environmental governance and higher innovation capacity jointly promote efficiency improvements. Rather than reflecting a simple "scale effect," Jiangsu's experience suggests that economic development translates into higher CEEWT only when coupled with effective institutional and technological mechanisms.

### 4.3.2 Second Echelon: Shanghai and Zhejiang Province

Shanghai and Zhejiang form the second echelon, exhibiting similarly high efficiency levels through distinct developmental pathways.

Shanghai's CEEWT performance is primarily driven by industrial restructuring and regulatory stringency. Early deindustrialization, a service-oriented economic structure, and the rapid diffusion of advanced wastewater treatment technologies have jointly reduced carbon intensity. These characteristics align with the technique effect in environmental economics, where cleaner production methods offset the environmental pressure associated with economic activity.

Zhejiang Province, by contrast, demonstrates a governance-oriented pathway. Through refined urban planning, decentralized wastewater treatment strategies, and regionally differentiated environmental policies, Zhejiang achieves relatively high efficiency despite lower fiscal capacity than Shanghai. This suggests that institutional design and spatially adaptive governance can partially substitute for economic scale advantages.

### 4.3.3 Third echelon: Inland and midstream provinces

The remaining provinces—Anhui, Sichuan, Chongqing, Hubei, Hunan, Jiangxi, Yunnan, and Guizhou—exhibit comparatively low CEEWT levels, generally ranging between 0.2 and 0.3.

These regions face a combination of constraints. First, industrial structures remain dominated by secondary industries with relatively high energy intensity. Second, limited fiscal resources restrict investments in advanced wastewater treatment technologies. Third, in provinces such as Sichuan and Chongqing, extensive ecological protection zones constrain industrial restructuring and infrastructure expansion, resulting in a trade-off between environmental conservation and efficiency gains.

Importantly, the observed pattern does not support a pollution haven hypothesis within the YEB, as low-efficiency regions do not benefit from systematically looser environmental regulation. Instead, the findings are more consistent with structural lock-in and capacity constraints, which hinder the diffusion of low-carbon technologies across less-developed regions.

## 4.4 Temporal dynamics, policy shocks, and convergence analysis

Figure 3 illustrates the temporal evolution of average CEEWT across the YEB. The most prominent fluctuation occurs during 2015–2017, when most provinces experienced a temporary decline in efficiency. This period coincides with the nationwide implementation of the Action Plan for Water Pollution Prevention and Control, which mandated rapid expansion and upgrading of wastewater treatment capacity.

In the short run, these policy-driven infrastructure investments increased treatment volumes and associated emissions, leading to a transitional efficiency loss. However, as facilities became operationally optimized, CEEWT rebounded, indicating a delayed efficiency payoff from regulatory intervention.

To formally assess convergence dynamics, σ-convergence and β-convergence tests were conducted using panel data methods (Supplementary Appendix A). The results suggest that while overall efficiency dispersion does not decline monotonically—indicating the absence of strong σ-convergence—there is evidence of conditional β-convergence, implying that provinces with lower initial efficiency tend to improve faster when controlling for structural characteristics. This finding supports the presence of conditional efficiency catch-up rather than unconditional convergence.

## 4.5 Jiangsu's resilience during the 2016 shock: an empirical perspective

Unlike most provinces, Jiangsu maintained continuous CEEWT growth during 2016. Rather than attributing this outcome solely to policy narratives, supplementary fixed-effects panel regressions reported in Supplementary Appendix D provide empirical support for the role of regulatory intensity and technological investment.

The regression results indicate that government R&D expenditure and environmental protection spending are significantly associated with higher CEEWT after controlling for province-specific and time-specific effects. These findings suggest that Jiangsu's resilience reflects a combination of pre-existing technological capacity, fiscal strength, and policy implementation efficiency, rather than a singular policy shock.

While causal inference remains beyond the scope of this study, the consistency between descriptive patterns and econometric associations enhances confidence in the proposed mechanisms.

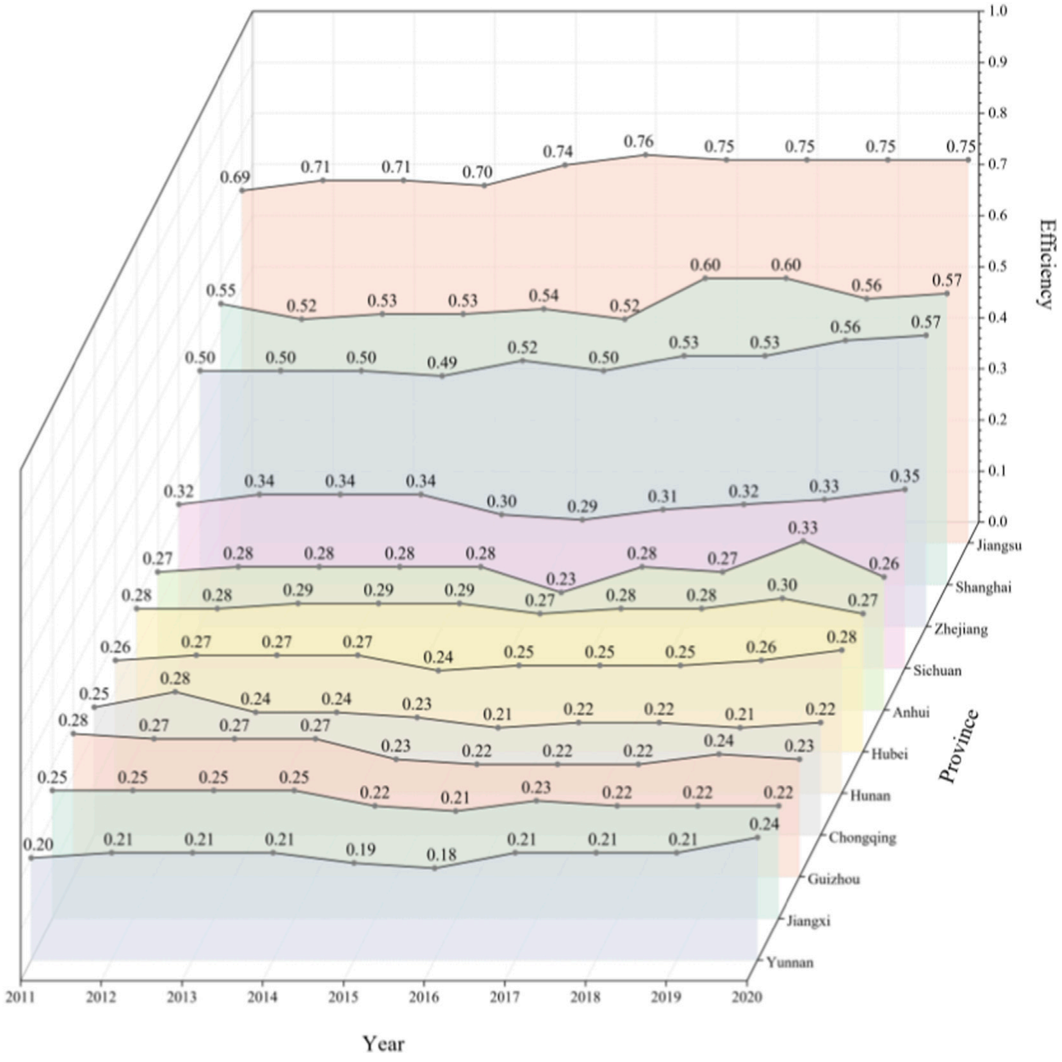


FIGURE 3
2011-2020 CEEWTYEB line chart.

## 4.6 Discussion and theoretical implications

Taken together, the results highlight that CEEWT in the YEB is shaped by multi-dimensional interactions among economic development, technological capability, industrial structure, and institutional design. Economic scale alone does not guarantee high efficiency; instead, efficiency gains materialize when development is accompanied by innovation-oriented governance and structural upgrading.

The findings contribute to the broader literature by demonstrating that low-carbon wastewater treatment efficiency exhibits conditional convergence, moderated by regional characteristics, and that policy-induced short-term efficiency losses may precede long-term gains. These insights underscore the importance of coordinated regional strategies to facilitate technology diffusion and institutional learning across heterogeneous regions.

# 5 Conclusion and policy implications

## 5.1 Conclusion

This study examines the spatiotemporal evolution of CEEWT in the Yangtze River Economic Belt using an entropy weight–TOPSIS framework combined with IPCC-based carbon accounting. The results show that CEEWT has generally improved over time, but with notable fluctuations and persistent regional disparities.

Significant spatial heterogeneity is observed across provinces, with downstream regions such as Jiangsu, Shanghai, and Zhejiang consistently outperforming upstream and midstream areas. These differences reflect cumulative advantages in economic capacity, technological accumulation, and institutional governance rather than short-term policy effects. No clear evidence of regional convergence is found, indicating that efficiency improvement remains path-dependent.

Methodologically, this study extends carbon efficiency analysis to the wastewater treatment sector at a large regional scale and clarifies the conceptual distinction between carbon emission efficiency and traditional environmental or energy efficiency. The entropy weight–TOPSIS approach provides a comprehensive and comparable assessment of multidimensional efficiency performance without implying direct causal relationships.

### 5.2 Policy implications

Given the differentiated efficiency patterns across the YEB, policy strategies should be region-specific. For leading regions (e.g., Jiangsu and Shanghai), policy priorities should focus on strengthening low-carbon technology leadership through stricter efficiency standards, advanced treatment technologies, and international cooperation. For intermediate regions (e.g., Zhejiang), improving coordination between urban development and wastewater systems, promoting circular economy practices, and enhancing operational optimization are key to sustaining efficiency gains. For lagging regions, targeted fiscal support, technical assistance, and cross-regional cooperation mechanisms are essential to address structural constraints and improve basic treatment capacity and operational performance. At the basin level, enhanced interregional coordination and differentiated regulation can support a more balanced low-carbon transition of wastewater treatment systems.

### 5.3 Limitations

Several limitations should be noted. First, carbon emissions were estimated using IPCC default parameters, which may not fully capture regional differences in wastewater characteristics and treatment technologies. Second, the entropy weight–TOPSIS method evaluates relative efficiency but does not identify causal relationships. Third, data constraints required the use of macro-level proxy indicators rather than plant-level technological variables. These limitations point to directions for future research as more detailed data become available.

## Data availability statement

The authors acknowledge that the data presented in this study must be deposited and made publicly available in an acceptable repository, prior to publication. Frontiers cannot accept a manuscript that does not adhere to our open data policies.

## Author contributions

XC: Writing – original draft, Data curation, Resources, Writing – review and editing. PJ: Writing – review and editing, Funding acquisition. XJ: Writing – review and editing, Methodology.. HC: Methodology, Writing – review and editing, Software.

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## Conflict of interest

The author(s) declared that this work was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

## Generative AI statement

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## Publisher's note

## Supplementary material

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fenvs.2026.1740795/full#supplementary-material

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