

Article

RETRACTED: Evaluating and Predicting Green Technology Innovation Efficiency in the Yangtze River Economic Belt: Based on the Joint SBM Model and GM(1,N| λ,γ) Model

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Abstract

Green technology innovation (GTI) is pivotal for driving energy transition and low-carbon development in manufacturing. This study evaluates the spatiotemporal efficiency and predicts trends of GTI in China's Yangtze River Economic Belt (YREB, 2010–2022) using a combined “input-desirable output-undesirable output” framework. Combining the SBM and super-efficiency SBM models, we evaluate regional GTI efficiency (2010–2022) and reveal its spatiotemporal patterns. An improved GM(1,N| λ,γ) model with a new information adjustment parameter (λ) and nonlinear parameter (γ) is applied for prediction. Key findings include: (1) The GTI efficiency remains generally low during the study period (provincial average: 0.7049–1.4526), showing an “east-high, west-low” spatial heterogeneity. Temporally, provincial efficiency peaked in 2016, with intensified fluctuations around 2020 due to policy iterations and external shocks. (2) Regional efficiency displays a stepwise decline pattern from downstream to middle-upstream areas. Middle-upstream regions face efficiency constraints from insufficient inputs and undesirable output redundancy, yet exhibit significant optimization potential. (3) Parameter analysis highlights that downstream provinces ($\gamma \approx 1$) exhibit mature green adoption, while mid-upstream regions (e.g., Hubei) face severe technological lock-in and reliance on traditional energy. Additionally, middle and downstream provinces (e.g., Sichuan, Anhui) with low λ values show rapid policy responsiveness, but face efficiency volatility from frequent shifts. (4) The improved GM(1,N| λ,γ) model shows markedly enhanced prediction accuracy compared to traditional grey models, effectively addressing the “poor-information, grey-characteristic” data trend extraction challenges in GTI research. Based on these findings, targeted policy recommendations are proposed to advance GTI development.

Keywords: green technology innovation; SBM model; super-efficiency SBM model; GM(1,N| λ,γ)



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1. Introduction

Under the dual drivers of global climate change and sustainable development goals, low-carbon transition has become a core global agenda [1], as shown in Figure 1. As the world's largest energy consumer and carbon emitter, China's historical high-energy-consumption development model has trapped its manufacturing sector in the initial phase of the Environmental Kuznets Curve, where economic growth intensifies environmental degradation, causing severe resource waste and ecological damage [2]. The “Made in China 2025” strategy prioritizes energy system restructuring, advocating clean energy systems and leveraging green technology innovation (GTI) to transform traditional manufacturing's energy metabolism patterns. This shift aims to break “high-carbon lock-in” and achieve a “zero-carbon leap” in energy consumption [3], offering systemic solutions for global industrial decarbonization [4].

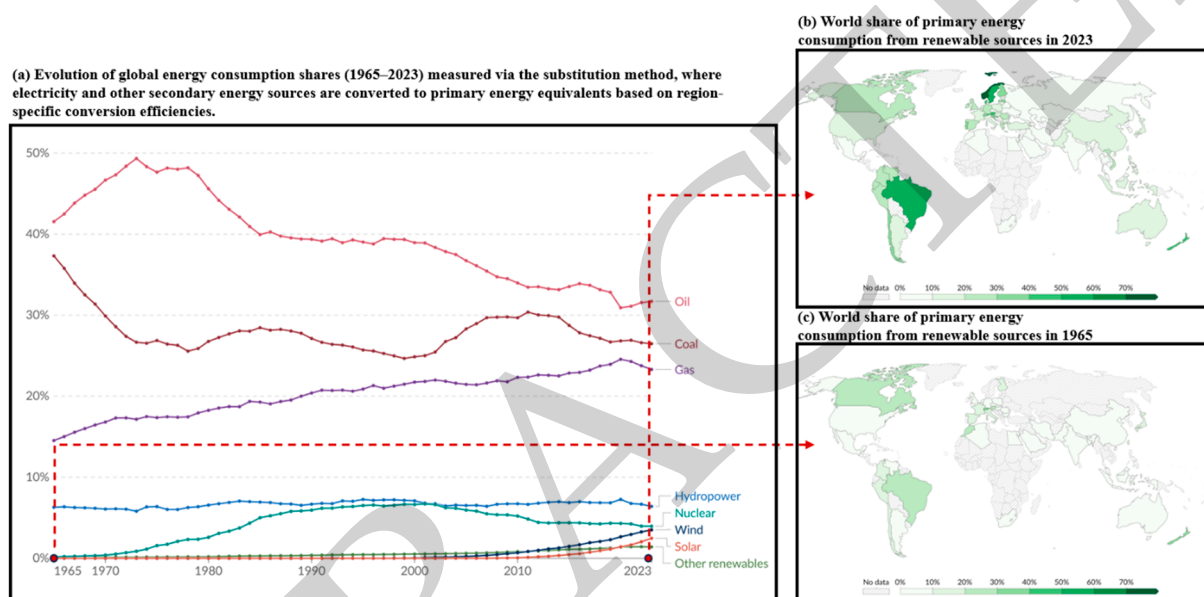


Figure 1. (a) Global energy consumption shares, 1965–2023. Calculated via the substitution method (primary energy equivalents). (b) World share of primary energy consumption from renewable sources, 2023. (c) World share of primary energy consumption from renewable sources, 1965. Source: Our World in Data, available at <https://ourworldindata.org/grapher>, accessed on 15 April 2025.

GTI, defined by the International Patent Classification (IPC) Expert Committee as innovations in environmentally harmless technologies, promotes resource conservation, pollution reduction, and circular utilization of materials [5]. As a foundational driver for achieving China's “dual carbon” goals, GTI has become pivotal for national decarbonization efforts [6]. However, challenges persist, including regional disparities in GTI efficiency and insufficient coordination of green innovation resources across China's manufacturing sector. The Yangtze River Economic Belt, a strategic manufacturing corridor spanning eastern, central, and western China, exemplifies these issues—its uneven GTI performance hampers regional synergy and weakens the nationwide carbon neutrality demonstration effect. The core problem lies in optimizing GTI resource allocation and enhancing cross-regional collaboration. Addressing this requires systematic analysis of regional GTI evolution patterns and the development of predictive efficiency models to strengthen green innovation systems and improve coordinated emission reduction mechanisms, thereby supporting high-quality development.

Building upon this context, this study addresses these pivotal research questions: How can the input-desirable output-undesirable output indicator system be used to evaluate

the GTI efficiency in the YREB? How can the grey model be effectively leveraged to predict the dynamic evolution of GTI efficiency in this region? To answer these questions, Section 3 details the modeling mechanism and computational framework of the proposed model. Section 4 analyzes the results of GTI efficiency evaluation and prediction, and discusses them further. Section 5 synthesizes core insights derived from the evaluation and prediction analysis, while focusing on the policy implications of the findings for advancing the transition towards sustainability. The main contributions of this paper are as follows:

1. Development of a multi-dimensional GTI efficiency evaluation framework. Unlike the single-perspective framework adopted by Jiang et al. (2013) and the input-output indicator system adopted by Dong et al. (2022), we integrate input, desirable output, and undesirable output into a unified system, while comprehensively considering and collecting various indicators, significantly improving the depth of evaluation (Sharif et al., 2023) [7–9].
2. Constructing the joint SBM model to break through the efficiency threshold, the SBM model and the super-efficiency SBM model are used in combination, overcoming the threshold problem inherent in using either model alone [10,11], so that GTI efficiency could be predicted more smoothly.
3. According to Tien's research [12], existing studies on GM(1,N) have encountered issues such as incorrect imitation and misuse. Therefore, to further enhance the accuracy and precision of the model process and results, this paper introduces the new information adjustment parameter λ and the nonlinear parameter γ into the GM(1,N) prediction model. Different from the MGM(1,m | λ, γ) of Wu et al. [13], MGM(1,m | λ, γ) requires a grey correlation degree of >0.5 . Our model is more practical with the help of their parameters, but without their requirements. At the same time, compared to the original model, this correction can more effectively capture the trend of GTI efficiency and allow more reasonable prediction.

2. Literature Review

2.1. Research on the Evaluation of GTI

The research focus on evaluating the efficiency of GTI primarily includes evaluation indicator systems and evaluation models. The evaluation of GTI is grounded in theories of total factor productivity. However, scholars diverge in their conceptualizations of GTI, leading to two dominant evaluation paradigms: The first, represented by Jiang et al. and Zhang et al. [7,14], adopts an input-oriented perspective, emphasizing resource allocation efficiency and aligning with the Resource-Based View (RBV) core tenet, that competitive advantage stems from the effective integration of key inputs. The second paradigm, championed by scholars including Li and Xiao, Popp, Qi et al., and Sharif et al. [9,15–17], employs an output-oriented framework. This approach further distinguishes between desirable outputs (e.g., green patents) and undesirable outputs (e.g., pollution emissions), rooted in eco-efficiency theory and aiming for synergistic enhancement of economic and environmental performance.

A significant debate centers on the trade-offs between simplicity and comprehensiveness in GTI indicator systems. Sharif et al. [9] proposed an objective criterion based on slow change to directly quantify innovation output (usually the number of green patent applications or grants) [15,18–20]. Alternatively, other scholars prefer to use an input-desirable output indicator system [8,21–24], which is currently the most widely used system for evaluating GTI efficiency. Recent advancements by Jin et al. [25], Tang et al. [26], and Wang et al. [27] systematically integrate environmental externality indicators, establishing a comprehensive three-dimensional framework encompassing inputs, desirable outputs, and undesirable outputs.

Methodologically, GTI efficiency evaluation predominantly relies on two technical pathways: Stochastic Frontier Analysis (SFA) and Data Envelopment Analysis (DEA) [28]. As a parametric method, SFA [29,30] requires predefined production function forms. In contrast, DEA [31], a non-parametric technique, holds distinct advantages in mitigating subjective specification bias, offering algorithmic flexibility, and handling complex multi-dimensional relationships [32]. This has established DEA as the mainstream tool for GTI efficiency assessment. Scholars [33–38] widely employ DEA for efficiency measurement, and, based on this, have innovated upon the traditional DEA model [39,40]. However, traditional DEA's proportional radial input-output assumptions may compromise accuracy. To address this limitation, Tone [11] proposed the Slacks-Based Measure (SBM) model, incorporating slack variables to enhance estimation precision. However, it has threshold limitations and cannot compare objects that reach the threshold.

2.2. Research on the Influencing Factors of GTI

Scholarly inquiry into the drivers of GTI has yielded substantial insights [41–43], identifying government policies and environmental regulations as pivotal factors. The impact of environmental regulation has garnered particular scrutiny. The “Porter Hypothesis” [44] posits that well-designed regulation can act as a catalyst for corporate technological innovation. Some studies [45,46] show that by designing appropriate environmental regulation tools (such as pollution taxes), not only can pollution emissions be reduced, but technological innovation in enterprises can also be significantly enhanced. However, some studies [47–49] have also found that environmental regulations may lead to a sharp increase in compliance costs, which may in turn suppress technological innovation efficiency. This contradictory phenomenon is particularly prominent in capital-intensive industries and those facing strict carbon constraints. Consequently, the net impact of environmental regulation on GTI remains a subject of ongoing academic debate, warranting deeper investigation.

The nexus between green finance and GTI has also been extensively examined. Research by Li et al. [50] validates the stimulative effect of green credit on clean technology innovation, subsequently fostering GTI. Focusing on green bonds, de Haas and Popov and Flammer analyze their pricing mechanisms and impact on corporate value, providing empirical evidence that green bond issuance spurs corporate green innovation [51,52]. It is particularly noteworthy that a close and distinctive interplay exists between green finance and manufacturing GTI, exerting a profound influence on its developmental trajectory.

2.3. Research Status of the Grey GM(1,N) Prediction Model

The GTI process exhibits distinct “poor-information, grey-characteristic” attributes. The GM(1,N) model [53] offers a methodological foundation for addressing the “poor-information” challenges in GTI systems with sparse data by analyzing interdependencies between system behavior variables and external drivers, a capability validated in financial forecasting [54–56]. Its ability to extrapolate trends from sparse datasets has driven applications in agriculture, environmental management, and energy transitions [57–59]. Structural optimizations by Abdulshahed et al., Wang et al., and Zhao and Guo [60–62] further enhanced its parameter estimation mechanisms, while hybrid integrations with statistical models [63,64] broadened its adaptability. However, the model's conventional linear framework struggles to reconcile the inherent “grey-characteristic” complexities of GTI systems, such as nonlinear interactions between technological innovation and ecological benefits or volatile policy-market dynamics. While innovations like the kernel-based KGM(1,n) [65] and parameter-optimized GMCO(1,N) [66] address nonlinearity, and the regularized R-GMC(1,N) [67] mitigates overfitting, these adaptations introduce compu-

tational trade-offs. Critics contend that such iterative modifications—though empirically validated in niche applications—risk over-engineering the framework, potentially obscuring its interpretability when applied to multifaceted GTI challenges like heterogeneous innovation metrics or fluctuating green credit policies.

3. Methodology and Dataset

3.1. Data Source and Processing

This study focuses on the YREB's 11 provincial-level regions (Shanghai, Jiangsu, Zhejiang, Anhui, Jiangxi, Hubei, Hunan, Chongqing, Sichuan, Guizhou, and Yunnan) from 2010 to 2022. This period comprehensively covers China's key green transition policy cycles, including the 12th–14th Five-Year Plans (2011–2025), the announcement of “Dual Carbon” goals (2020), and the COVID-19 impact, enabling analysis of policy impacts and external shocks on green technology innovation. Data for manufacturing GTI efficiency evaluation were collected from national statistical yearbooks (technology, energy, environment) and regional statistical sources, supplemented by the Belt's big data platform. The year 2010 marks the standardization of green patent classification under the IPC system in China, while 2022 is the latest year with complete data availability. Missing values were addressed through interpolation techniques [68]. The amount of data not only ensures the stability of the estimation of the front surface, but also satisfies the characteristics of “poor-information, grey-characteristic” of the grey prediction model.

3.2. Establishment of the Evaluation Model

As highlighted in Section 2.1, conventional DEA models inadequately address two critical limitations for GTI evaluation: (1) neglect of non-radial slack variables in input–output relationships, leading to biased efficiency estimates, and (2) their rigid efficiency ceiling of 1 obscures performance distinctions among top-performing regions. To resolve these gaps, our integrated framework combines the non-radial SBM and super-efficiency SBM models. This dual approach achieves three goals: (1) enabling nuanced regional comparisons by eliminating efficiency thresholds; (2) removing threshold restrictions facilitates better prediction of GTI efficiency; and (3) identifying inefficiencies in pollution control and resource allocation to guide targeted policies. By aligning with the “input–desirable–undesirable output” paradigm established in prior research, the model advances GTI evaluation toward both theoretical robustness and practical applicability. The process of evaluating the GTI efficiency in this section is shown in Figure 2.

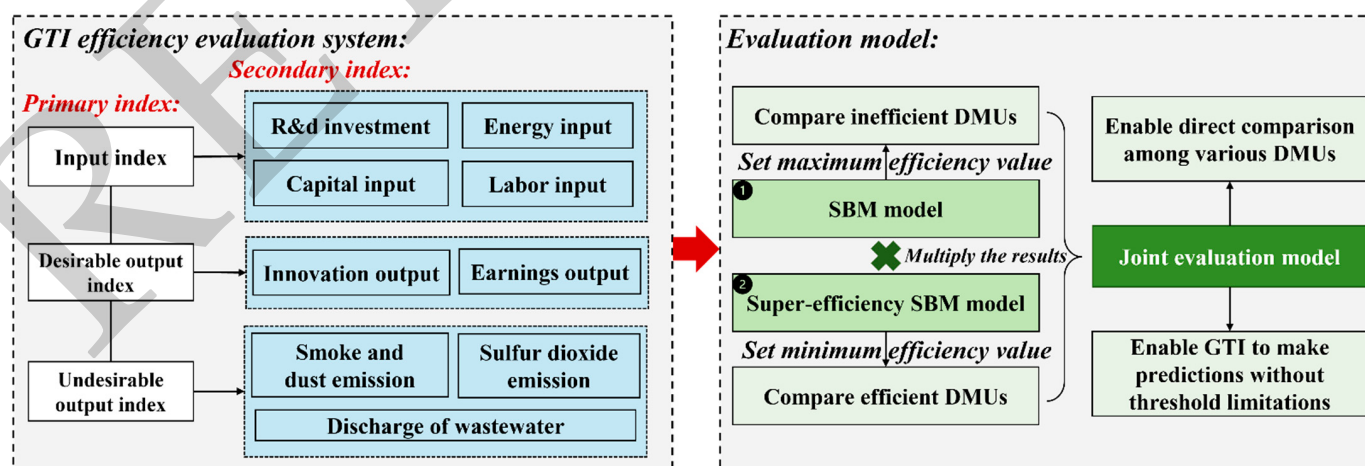


Figure 2. The evaluation process of GTI efficiency.

3.2.1. Construction of the Evaluation Indicator System

The indicator selection for assessing manufacturing GTI efficiency in the YREB adheres to three core principles:

(1) Scientific Rigor

Utilizing authoritative data from national statistical yearbooks, the chosen indicators objectively measure GTI efficiency development and regional disparities in China's manufacturing sector.

(2) Theoretical–Practical Balance

Drawing from academic literature and regional industrial challenges, the framework emphasizes data accessibility and indicator representativeness to capture both current status and future potential.

(3) Operational Feasibility

Considering the study's extensive scope and data acquisition challenges, the indicators ensure cross-regional and temporal comparability for effective GTI efficiency analysis.

Guided by total factor productivity theory and the aforementioned principles, this study establishes an evaluation framework for GTI efficiency structured around three core dimensions: input, desirable output, and undesirable output. The framework comprises these three primary dimensions and nine specific secondary indicators in Table 1 (indicator abbreviations in parentheses).

Table 1. Evaluation index system of GTI efficiency.

First Grade Indexes	Second Grade Indexes	Definition	Unit
Input	R&D input (<i>Rad_in</i>)	Internal expenditure of R&D funds	10 K CNY
	Energy input (<i>Ene_in</i>)	Total energy consumption in manufacturing	tce
	Capital input (<i>Cap_in</i>)	Net fixed assets of manufacturing enterprises above designated size	100 M CNY
	Labor input (<i>Lab_in</i>)	R&D personnel full-time equivalent	man-year
Desirable output	Innovation output (<i>Inn_eo</i>)	Number of green invention patents granted	pc
	Earnings output (<i>Pro_eo</i>)	Manufacturing products operating income	10 K CNY
Undesirable output	Smoke and dust emissions (<i>Smo_eo</i>)	Industrial “three wastes” emissions or production amount	10 k t
	Sulfur dioxide emissions (<i>So2_eo</i>)		10 k t
	Wastewater discharge (<i>Was_eo</i>)		10 k t

(1) Input

The input dimension encompasses four secondary indicators: capital input, energy input, R&D input, and labor input. Labor and capital represent fundamental resources underpinning GTI activities in manufacturing. To accurately gauge human capital investment, this study employs the full-time equivalent (FTE) of R&D personnel. This metric offers a more objective reflection of actual R&D effort than simple headcounts. Capital input is represented by the net value of fixed assets in large-scale manufacturing enterprises. R&D input is measured by internal R&D expenditure, indicating both the regional commitment to technological innovation and the sustainability of GTI efforts. Energy input utilizes the

total energy consumption of the manufacturing sector, serving to assess resource intensity and associated environmental impacts.

(2) Desirable output

Desirable outputs are assessed through innovation outcomes and economic profits. Patents, as the primary tangible output of green innovation knowledge creation, serve as a key metric for innovation output. Given the superior technological content, innovation level, and market value of invention patents, granted green invention patents are selected to represent the potential and efficiency of GTI innovation output. Recognizing the time lag in patent commercialization and their incomplete reflection of realized market value, manufacturing product sales revenue is additionally incorporated as a measure of direct economic returns from GTI.

(3) Undesirable output

Undesirable output focuses on environmental pressures arising from production. Industrial pollution is quantified using data on the “three wastes” (wastewater, gaseous emissions, solid waste). To address regional discrepancies in industrial gaseous emissions reporting (e.g., Yunnan and Guizhou primarily report key pollutants SO₂, NO_x, and soot/dust, while other regions report total emissions including CO₂), industrial sulfur dioxide (SO₂) emissions are uniformly adopted as the representative indicator to ensure data comparability.

The trends in the data for the nine secondary indicators are shown in Figure 3.

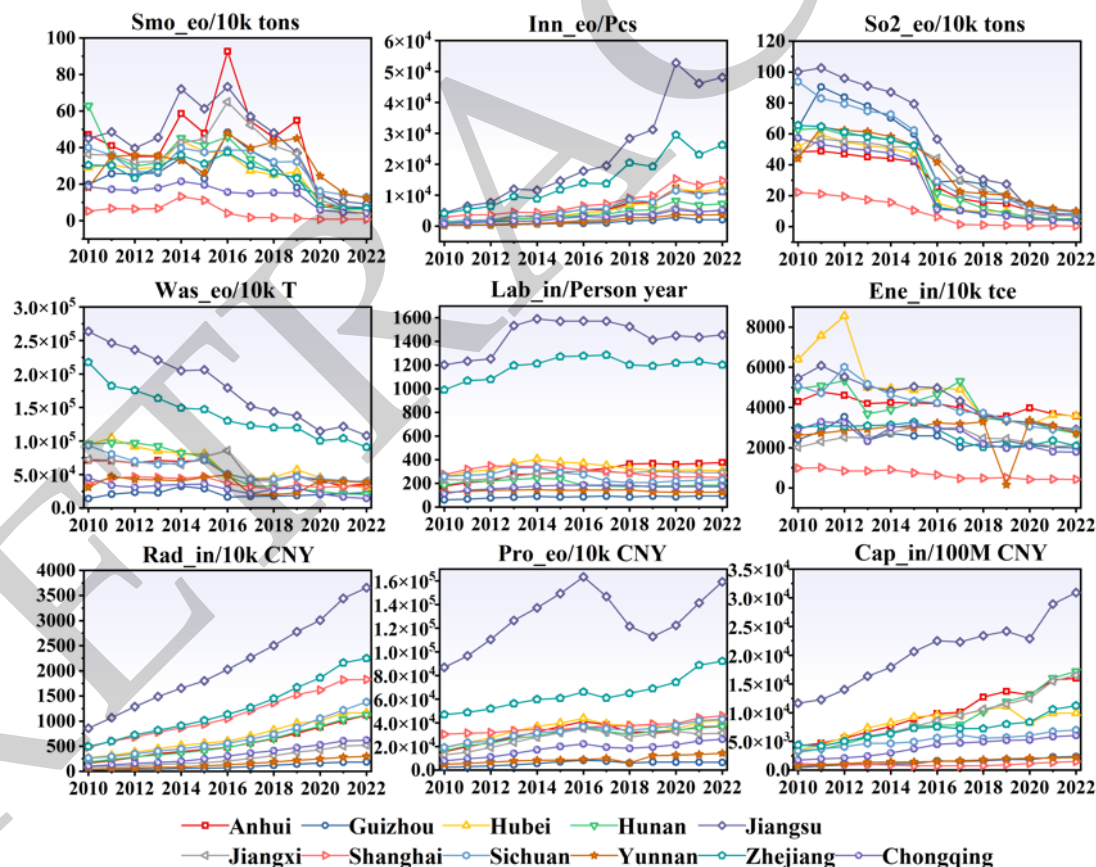


Figure 3. Trends in data on indicators of GTI.

3.2.2. Undesirable Output SBM Model

Tone [11] built the undesirable output SBM model based on the original SBM model [10], which introduced the undesirable output index and considered both economic benefit and environmental impact [69].

Considering there are n decision-making units, with the number j of the unit being $DMU_j, j = 1, 2, \dots, n$. Each decision-making unit incorporates three fundamental elements: input, desirable output, and undesirable output. These elements are each represented by a corresponding vector (X, Y, Z) :

$X = (x_{rj}) \in R^{s_0 \times n}, Y = (y_{wj}) \in R^{s_1 \times n}, Z = (z_{lj}) \in R^{s_2 \times n}$, where x_{rj} represents the actual data of the input indicator for the number j of the decision-making unit DMU_j , y_{wj} represents the actual data of the number w of the desirable output indicator for the number j of the decision-making unit DMU_j , and z_{lj} represents the actual data of the number l of the undesirable output indicator for the number j of the decision-making unit. Here, s_0, s_1 , and s_2 represent the numbers of input indicators, desirable output indicators, and undesirable output indicators, respectively.

Simultaneously, let $X > 0, Y > 0, Z > 0$, then the feasible set P is formed as:

$$P = \{(x, y, z) | x \geq XA, y \leq YA, z \geq ZA, A \geq 0\} \quad (1)$$

where A represents a weight vector, $A = [\lambda_1, \lambda_2, \dots, \lambda_n] \in R^n$, with λ_n representing the weight of the number n of decision-making unit; $x \geq XA$ indicates that the actual input level x is greater than or equal to the projected input level; $y \leq YA$ indicates that the actual desirable output y is less than or equal to the projected desirable output level; $z \geq ZA$ indicates that the actual undesirable output z is greater than or equal to the projected undesirable output level.

The SBM model with undesirable outputs is represented as:

$$\rho_1 = \min \frac{1 - \frac{1}{s_0} \sum_{r=1}^{s_0} \frac{s_r^x}{x_{r0}}}{1 + \frac{1}{s_1 + s_2} \left(\sum_{w=1}^{s_1} \frac{s_w^y}{y_{w0}} + \sum_{l=1}^{s_2} \frac{s_l^z}{z_{l0}} \right)} \quad (2)$$

$$\text{s.t.} \begin{cases} x_{r0} = \sum_{j=1}^n \lambda_j x_j + s_r^x, \forall r \\ y_{w0} = \sum_{j=1}^n \lambda_j y_j - s_w^y, \forall w \\ z_{l0} = \sum_{j=1}^n \lambda_j z_j + s_l^z, \forall l \\ s_r^x \geq 0, s_w^y \geq 0, s_l^z \geq 0, \lambda_j \geq 0, \forall r, j, w, l \end{cases}$$

where s_r^x and s_l^z represent the surplus of the number r of the input indicator and the surplus of the number l of the undesirable output, respectively. s_w^y represents the shortage of the number w of the desirable output, $s_r^x \in R^{s_0}, s_l^z \in R^{s_2}, s_w^y \in R^{s_1}$; x_{r0}, y_{w0} , and z_{l0} are intermediate parameters in the model. ρ_1 represents the efficiency value of the decision-making unit in the undesirable output SBM model, and $\rho_1 \leq 1$.

3.2.3. Undesirable Output Super-Efficiency SBM Model

Aiming at the problem that the upper limit of DMU efficiency value is strictly limited to 1 by the traditional undesirable output SBM model, which makes it impossible to distinguish the efficiency difference of DMU on the front plane effectively, this paper further adopts the improved undesirable output super-efficiency SBM model for calculation. By removing the upper limit constraint of efficiency value, the efficiency value of effective DMU breaks the threshold limit of 1, so as to realize the fine distinction and scientific prediction of the efficiency level of frontier units. The super-efficiency SBM model assumes the same as the SBM model. The super-efficient SBM model with undesirable outputs is:

$$\rho_2 = \min \frac{1 + \frac{1}{s_0} \sum_{r=1}^{s_0} \frac{s_r^x}{x_{r0}}}{1 - \frac{1}{s_1 + s_2} \left(\sum_{w=1}^{s_1} \frac{s_w^y}{y_{w0}} + \sum_{l=1}^{s_2} \frac{s_l^z}{z_{l0}} \right)}$$

$$\text{s.t.} \begin{cases} x_{r0} \geq \sum_{j=1, \neq 0}^n \lambda_j x_j - s_r^x, \forall r \\ y_{w0} \leq \sum_{j=1, \neq 0}^n \lambda_j y_j + s_w^y, \forall w \\ z_{l0} \geq \sum_{j=1, \neq 0}^n \lambda_j z_j - s_l^z, \forall l \\ 1 - \frac{1}{s_1 + s_2} \left(\sum_{w=1}^{s_1} \frac{s_w^y}{y_{w0}} + \sum_{l=1}^{s_2} \frac{s_l^z}{z_{l0}} \right) > 0 \\ s_r^x \geq 0, s_w^y \geq 0, s_l^z \geq 0, \lambda_j \geq 0, \forall r, j, w, l \end{cases} \quad (3)$$

where ρ_2 is used to represent the efficiency value calculated by the undesirable super-efficiency SBM model, and $\rho_2 \geq 1$.

3.2.4. Joint Evaluation Model

Guided by the principle of comprehensiveness [70], reliance on a single evaluation model can induce bias through its inherent assumptions, whereas a combined approach integrates efficiency assessments from multiple angles. The SBM model quantifies inefficiency by establishing an upper bound on efficiency scores. In contrast, the super-efficiency SBM variant enables comparative assessment of efficient DMUs by relaxing the lower bound constraint. To overcome the limitations inherent in individual models and establish a comprehensive efficiency measurement system, this study develops an integrated evaluation model. The computational framework for this model is defined as follows:

$$\rho^* = \rho_1 \times \rho_2 \quad (4)$$

This joint model satisfies the following properties:

- (1) Monotonicity: If ρ_1 or ρ_2 increases, ρ^* will also increase accordingly, aligning with the intuitive requirements of efficiency evaluation.
- (2) Robustness: The multiplicative form mitigates the impact of extreme values from a single model, avoiding overreliance on specific slack variables.
- (3) Interpretability:
 - $\rho^* > 1$ indicates that a DMU excels in both pollution control and frontier competitiveness, suggesting a focus on enhancing the marginal benefits of technological innovation.
 - $\rho^* < 1$ reflects dual inefficiency, necessitating prioritized improvements in input redundancy or pollution control.

3.3. Establishment of the Prediction Model

3.3.1. Theoretical Support

Wu et al. [13] introduced the MGM(1,m | λ, γ) model, representing the inaugural integration of the new information adjustment coefficient λ and the background value nonlinear coefficient γ within a grey system framework. While the MGM(1,m | λ, γ) model is designed for multivariate time series forecasting, it mandates that the grey relational grade between each dependent variable exceeds 0.5 and operates without accounting for external influencing factors. In the present study, however, the calculated grey relational grades for GTI efficiency across provinces and municipalities fall below this required threshold. Furthermore, the analysis necessitates consideration of additional determinants influencing GTI. Consequently, this research develops a GM(1,N | λ, γ) model by incorporating the new

information adjustment coefficient λ and the background value nonlinear coefficient γ into the foundational GM(1,N) model structure.

The improved GM(1,N | λ, γ) model integrates two critical theoretical perspectives to address the dynamic complexity of GTI systems:

(1) Policy Responsiveness and Information Asymmetry: Drawing on information economics [71], the new information adjustment parameter λ operationalizes the “policy feedback loop” mechanism proposed by policy iteration theory [72]. Specifically, $\lambda \in (0,1]$ quantifies the decay rate of historical policy inertia in GTI systems. Lower λ values indicate rapid assimilation of policy shocks—such as the 2020 pandemic-induced carbon neutrality acceleration—aligning with the “new information priority” principle. In addition, this mirrors dynamic capabilities [73] at the enterprise level: λ captures how enterprises “sense” abrupt policy changes (such as changing emission standards) and “reconfigure” innovation portfolios through real-time R&D reallocation.

(2) The nonlinear background value parameter γ embeds technology lock-in theory [74] into grey modeling. A higher $|\gamma - 1|$ indicates a path dependence trap: according to the “carbon lock-in” hypothesis [75], traditional investments in coal technology limit the adoption of renewable energy (with less input and more undesirable output). At the same time, it implies that the innovation ecosystem needs to enhance its self-regulation ability and there is further room for optimization. For objects with $|\gamma - 1|$ approaching 0, they have more advantages compared to other objects, such as their existing green patents and infrastructure creating increasing returns [44].

At the most intuitive application level, introducing new information adjustment parameter λ and nonlinear parameter γ into the GM(1, N) model also takes into account the following two factors: First, GTI is characterized by “poor-information, grey-characteristic”, and since traditional SBM and super-efficiency SBM models rely solely on historical data for efficiency evaluation, the new information adjustment parameter becomes crucial for real-time optimization. Following the principle of new information priority [76], this parameter effectively mitigates the volatility and mutation in GTI efficiency caused by policy shifts, technological breakthroughs, and external shocks. Taking an external shock like COVID-19 as an example, when there are external shocks such as COVID-19, the λ adjustment parameter rapidly responds to the sudden changes in efficiency induced by COVID-19 by assigning lower weights to historical observations (data from the COVID-19 period and before), thereby reducing the inertial influence of historical data. This demonstrates the pivotal role of the “new information priority” principle in absorbing unexpected disturbances. Second, the complex and diversified characteristics of GTI data necessitate the background value nonlinear parameter γ to better capture data nonlinearity. This dual enhancement allows the model to fully utilize data information while improving GTI efficiency prediction capability.

3.3.2. Selection of the Influencing Factors Indicators

In GTI efficiency evaluation, the evaluation indicators are primarily designed to gauge the actual outcomes and resource utilization efficiency of technological innovation activities, whereas the influencing factor indicators are intended to identify key drivers that constrain or enhance GTI efficiency. The two are distinct but interrelated. Based on the existing research content in Section 2.2, this chapter considers three dimensions: environmental regulation, green finance, and government policy.

(1) Environmental Regulation

The environmental regulation dimension is assessed through both formal and informal mechanisms. Formal regulation employs two indicators: industrial pollution control investment (in billions of yuan) and industrial added value (in billions of yuan). Informal

regulation utilizes four indicators: per capita income level (yuan), education level (percentage), population density (persons per square kilometer), and age structure (percentage). Consequently, six indicators collectively represent this dimension.

(2) Green Finance

Green finance is measured using seven key metrics: green credit (ratio of environmentally-focused project loans to total provincial lending), green investment (environmental control investment as a percentage of GDP), green insurance (share of pollution liability insurance premiums within total insurance), green bonds (proportion of eco-friendly bonds in total issuance), green support (environmental protection expenditure as a share of the total budget), green funds (market value ratio of sustainability-focused funds to total funds), and green equity (trading volume of carbon, energy, and emission rights relative to total equity transactions).

(3) Government Policy

In the government policy dimension, this study selects keywords related to environmental protection, environmental pollution, energy consumption, development philosophy, green production, green living, green ecology, and green construction from government reports of each province and city. The quantification metric is derived from the frequency of these keywords relative to the total word count in official government documents.

In summary, this study uses 14 indicators as the influencing factors of GTI efficiency, which include industrial pollution control investment, industrial added value, income level, education level, population density, age structure, green credit, green investment, green insurance, green bonds, green support, green equity, and government policy.

The trends of some of the above indicators (green credit-*Gcp*, green investment-*Giv*, green insurance-*Gis*, green bonds-*Gbo*) are shown in Figure 4.

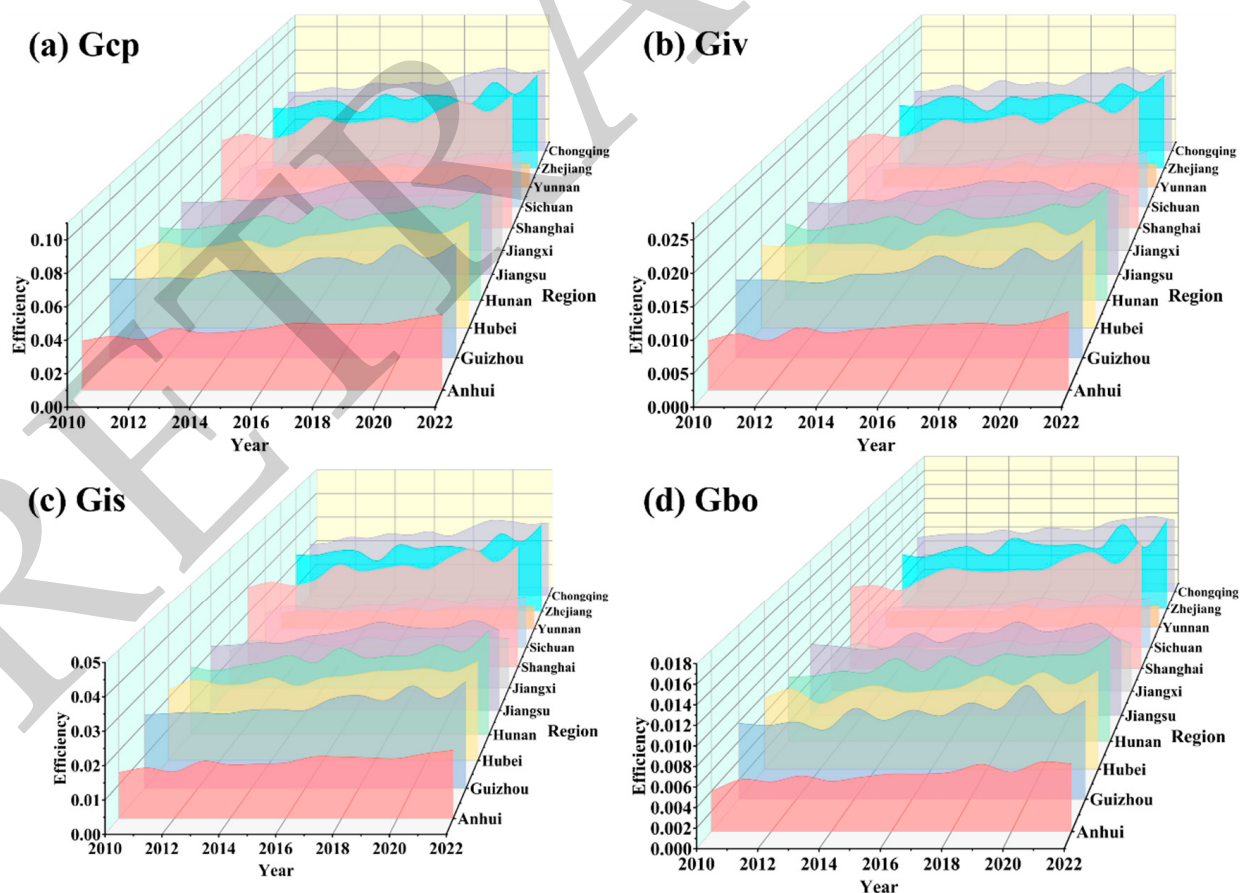


Figure 4. Trends in selected indicators of impact factors. (a) *Gcp*; (b) *Giv*; (c) *Gis*; (d) *Gbo*.

3.3.3. Modeling Mechanism

Let $Y^{(0)} = \{Y^{(0)}(1), Y^{(0)}(2), \dots, Y^{(0)}(n)\}^T$ be the system characteristic matrix, where $Y^{(0)}(k)$ represents the technological efficiency of the number k of the green innovation for individual provinces or cities, $k = 1, 2, \dots, n$;

The related factor sequence is:

$$\begin{aligned} X_2^{(0)} &= \{x_2^{(0)}(1), x_2^{(0)}(2), \dots, x_2^{(0)}(n)\}^T \\ X_3^{(0)} &= \{x_3^{(0)}(1), x_3^{(0)}(2), \dots, x_3^{(0)}(n)\}^T \\ &\dots\dots\dots \\ X_N^{(0)} &= \{x_N^{(0)}(1), x_N^{(0)}(2), \dots, x_N^{(0)}(n)\}^T \end{aligned} \quad (5)$$

Among them, $X_i^{(0)}$ represents the influencing factor of the number i of the GTI efficiency, $x_i^{(0)}(k)$ represents the specific data of the year k of the number i of the influencing factor element; $X_i^{(1)} = \{x_i^{(1)}(1), x_i^{(1)}(2), \dots, x_i^{(1)}(n)\}^T$ is the first-order accumulated series of $X_i^{(0)}$, the number u of the element in the first-order accumulated series $x_i^{(1)}(k) = \sum_{g=1}^k x_i^{(0)}(g)$, $k = 1, 2, \dots, n; i = 2, 3, \dots, N; g = 1, 2, \dots, u$.

$Y_\lambda^{(1)}$ is the first-order accumulated series of system characteristic sequence $Y^{(0)}$ after adding the new information adjustment parameter λ , expressed as $Y_\lambda^{(1)} = \{y_\lambda^{(1)}(1), y_\lambda^{(1)}(2), \dots, y_\lambda^{(1)}(n)\}^T$, $\lambda \in (0, 1]$, $y_\lambda^{(1)}(k)$ represents the number k of the element in the first-order accumulated series $Y_\lambda^{(1)}$, among which the units are expressed as:

$$\begin{cases} y_\lambda^{(1)}(1) = y^{(0)}(1), k = 1 \\ y_\lambda^{(1)}(k) = y^{(0)}(k) + \lambda \cdot y_\lambda^{(1)}(k-1) = y^{(0)}(k) + \lambda \cdot \sum y^{(0)}(k-1), k = 2, 3, \dots, n \end{cases} \quad (6)$$

The neighborhood mean generated sequence $Y_\lambda^{(1)}$ is $Z^{(1)} = \{z^{(1)}(2), z^{(1)}(3), \dots, z^{(1)}(n)\}^T$.

The number k of the element in $Z^{(1)}$ is $z^{(1)}(k) = \left(\frac{y_\lambda^{(1)}(k) + y_\lambda^{(1)}(k-1)}{2} \right)^\gamma$, $k = 2, 3, \dots, n$, $\gamma > 0$, where γ is a nonlinear parameter with background value.

Based on the GM(1,N) model, the continuous new information priority multivariate grey model GM(1,N| λ, γ) is defined as:

$$\frac{dy_\lambda^{(1)}(t)}{dt} + ay_\lambda^{(1)}(t) = \sum_{k=2}^N b_k x_k^{(1)}(t) \quad (7)$$

After discretization, we get:

$$y^{(0)}(k) + az_1^{(1)}(k) = \sum_{i=2}^N b_i x_i^{(1)}(k) \quad (8)$$

where $-a$ is the system development coefficient, $b_i x_i^{(1)}(k)$ is the driving term, and b_i is the number i of the driving coefficient. And $\hat{a} = (a, b_2, \dots, b_N)^T$ is the parameter column vector.

Let:

$$M = \begin{pmatrix} -z^{(1)}(2) & x_2^{(1)}(2) & \cdots & x_N^{(1)}(2) \\ -z^{(1)}(3) & x_2^{(1)}(3) & \cdots & x_N^{(1)}(3) \\ \vdots & \vdots & \ddots & \vdots \\ -z^{(1)}(n) & x_2^{(1)}(n) & \cdots & x_N^{(1)}(n) \end{pmatrix} = \begin{pmatrix} -\left(\frac{y_\lambda^{(1)}(2)+y_\lambda^{(1)}(1)}{2}\right)^\tau & x_2^{(1)}(2) & \cdots & x_N^{(1)}(2) \\ -\left(\frac{y_\lambda^{(1)}(3)+y_\lambda^{(1)}(2)}{2}\right)^\tau & x_2^{(1)}(3) & \cdots & x_N^{(1)}(3) \\ \vdots & \vdots & \ddots & \vdots \\ -\left(\frac{y_\lambda^{(1)}(n)+y_\lambda^{(1)}(n-1)}{2}\right)^\tau & x_2^{(1)}(n) & \cdots & x_N^{(1)}(n) \end{pmatrix}, \quad (9)$$

$$G = \begin{pmatrix} y_\lambda^{(1)}(2) - y_\lambda^{(1)}(1) \\ y_\lambda^{(1)}(3) - y_\lambda^{(1)}(2) \\ \vdots \\ y_\lambda^{(1)}(n) - y_\lambda^{(1)}(n-1) \end{pmatrix} = \begin{pmatrix} \left(y^{(0)}(2) + \lambda \cdot y^{(0)}(1)\right) - y^{(0)}(1) \\ \left(y^{(0)}(3) + \lambda \cdot \sum y^{(0)}(2)\right) - \left(y^{(0)}(2) + \lambda \cdot y^{(0)}(1)\right) \\ \vdots \\ \left(y^{(0)}(n) + \lambda \cdot \sum y^{(0)}(n-1)\right) - \left(y^{(0)}(n-1) + \lambda \cdot \sum y^{(0)}(n-2)\right) \end{pmatrix}$$

where M and G are system matrix and constant matrix, respectively, then the parameter vector $\hat{a} = (a, b_2, \dots, b_N)^T$ can be estimated by the least squares method $\hat{a}$ as: $\hat{a} = (M^T M)^{-1} M^T G$.

Considering $\sum_{i=2}^N b_i x_i^{(1)}(k)$ as a grey constant, then the near-time response form of the new information priority fractional order grey prediction model GM(1,N| λ, γ) is:

$$\hat{y}_\lambda(i) = (y_\lambda^{(1)}(0) - \frac{1}{a} \sum_{k=2}^N b_k x_k^{(1)}(i)) e^{-a(i-1)} + \frac{1}{a} \sum_{k=2}^N b_k x_k^{(1)}(i), i = 1, 2, \dots, n \quad (10)$$

where $\hat{y}_\lambda(k)$ is the accumulated value of the number k of released technology innovation efficiency, and $y_\lambda^{(1)}(0)$ is taken as $y_\lambda^{(1)}(1)$;

The reduction formula is:

$$\hat{y}^{(0)}(k) = \hat{y}_\lambda^{(1)}(k) - \lambda \hat{y}_\lambda^{(1)}(k-1), k = 1, 2, \dots, n \quad (11)$$

where $\hat{y}^{(0)}(k)$ is the reduction value of the number k of the GTI efficiency.

3.3.4. Parameter Optimization

The model's estimation of the first-order cumulative generation sequence and parameter matrix is significantly influenced by the settings of the new information adjustment parameter (λ) and the nonlinear parameter (γ). Given this critical dependency, optimal λ and γ values must be identified before undertaking subsequent modeling steps. To achieve this, the present study formulates parameter estimation as an optimization problem aimed at minimizing average error. The solution to this minimization problem is obtained via an iterative optimization algorithm.

$$\operatorname{argmin}_{\lambda, \gamma} \frac{1}{n} \sum_{k=1}^n \left| \frac{\hat{y}^{(0)}(k) - y^{(0)}(k)}{y^{(0)}(k)} \right| \times 100\% \quad (12)$$

3.3.5. Model Accuracy Test

Model performance evaluation and precision verification in this study utilize two key error metrics: Absolute Percentage Error (APE) and Mean Absolute Percentage Error (MAPE). The mathematical expressions for computing these metrics are:

$$APE = \left| \frac{y^{(0)}(k) - \hat{y}^{(0)}(k)}{y^{(0)}(k)} \right| \times 100\% \quad (13)$$

$$MAPE = \frac{1}{n} \sum_{k=1}^n \left| \frac{y^{(0)}(k) - \hat{y}^{(0)}(k)}{y^{(0)}(k)} \right| \times 100\% \quad (14)$$

Building upon the classification schema established by Wu et al. (2022b), we recalibrated the accuracy criteria into four new tiers specifically for GTI data characteristics. The revised threshold definitions are presented in Table 2.

Table 2. Prediction accuracy of GTI corresponding to MAPE.

MAPE (%)	Model Accuracy
<3	Excellent
3~10	Dependable
10~30	Qualified
>30	Deficient

4. Results and Discussion

This study employs the joint SBM model, as well as a manufacturing GTI efficiency evaluation index system, to evaluate the GTI efficiency of the manufacturing industry in 11 provinces and cities along the YREB from 2010 to 2022, and generate an efficiency index sequence reflecting the allocation and output status of regional GTI resources. Considering the inherent “information scarcity” of the GTI system and the system evolution characteristics of time series, this study takes GTI as the core input of GM(1, N| λ , γ), and combines external driving factors such as environmental regulation, green finance, and government policies to jointly guide the prediction process. This design follows the theoretical framework of “system behavior variables driving factor variables”, ensuring temporal consistency of predictions while improving policy interpretability and practicality of results.

4.1. Evaluating of the GTI Efficiency

Leveraging a joint SBM evaluation model and a manufacturing-specific GTI efficiency index system, the GTI efficiency of the manufacturing industry was assessed for 11 provinces and cities along the YREB over the period 2010–2022. The analysis, implemented in MATLAB R2024a, yielded the results compiled in Table 3. The overall mean GTI efficiency across the 11 regions and 11 years reached 0.9768. Moreover, distinct spatial patterns and temporal fluctuations characterize the efficiency values observed.

Table 3. Efficiency of GTI in the YREB.

DMU	2010	2011	2012	2013	2014	2015	2016
Shanghai	1.4248	1.3613	1.3548	1.3623	1.4127	1.4664	1.4762
Jiangxi	1.0625	1.0852	1.1018	1.1069	1.1136	1.1105	1.0997
Zhejiang	1.0902	1.0918	1.084	1.0878	1.0742	1.0824	1.1578
Jiangsu	1.0376	1.0474	1.0584	1.0605	1.0624	1.0727	1.0733
Hunan	1.0089	1.0098	1.0055	1.0232	1.0099	1.0137	1.0716
Chongqing	1.0231	1.0286	1.0313	1.0191	1.0079	1.0195	1.0303
Sichuan	0.4021	0.7255	0.5157	1.001	0.6591	1.0094	1.0388
Yunnan	1.0121	1.0061	1.0089	0.5025	1.0098	0.4855	0.4507
Anhui	1.0092	1.0445	1.0494	1.0407	1.0673	1.0606	1.0482

Table 3. Cont.

DMU	2010	2011	2012	2013	2014	2015	2016
Guizhou	0.3908	0.3837	0.3980	1.0304	1.0315	1.0923	1.0345
Hubei	0.3889	0.4504	0.4658	0.5901	0.5544	0.6287	1.0073
DMU	2017	2018	2019	2020	2021	2022	Ranking
Shanghai	1.5572	1.5406	1.5531	1.4737	1.4536	1.4472	1
Jiangxi	1.0949	1.0987	1.0885	1.0941	1.0650	1.0090	2
Zhejiang	1.0779	1.1294	1.1095	1.0613	1.0405	1.0374	3
Jiangsu	1.0673	1.0471	1.0679	1.0977	1.1034	1.0785	4
Hunan	1.0304	1.0212	1.0446	1.0442	1.0335	1.0017	5
Chongqing	0.6314	0.6445	0.7971	0.7584	1.0265	1.0207	6
Sichuan	1.0685	1.1198	1.0736	1.0448	1.043	1.0143	7
Yunnan	1.0025	0.5383	1.1727	1.0334	1.0274	1.0192	8
Anhui	1.0202	0.6385	0.5759	0.5043	0.4725	0.4690	9
Guizhou	1.0297	1.0153	1.0150	1.0010	0.3761	0.3689	10
Hubei	1.0033	1.0122	0.8499	0.6039	0.8075	0.8012	11

4.1.1. Spatial Dynamics of GTI Efficiency

Further analysis of GTI efficiency's spatial distribution along the YREB (Figure 5) segments the basin into upstream, midstream, and downstream regions. The downstream region, encompassing Shanghai (1.4526), Jiangsu (1.0672), and Zhejiang (1.0865), attains a mean efficiency of 1.2021, the highest among the three regions. This region leads in GTI efficiency, primarily due to its strong economic power (high capital input) and abundant research resources (high R&D input). The midstream region has a generally favorable development level of GTI, with Jiangxi (1.0870), Hunan (1.0245), Anhui (0.8426), and Hubei (0.7049) having an average efficiency of 0.9148. Although this region faces constraints such as insufficient financial input and weak technology, it is gradually releasing its development potential due to abundant labor resources (high labor input) and the dual support of an optimized innovation environment and infrastructure upgrades. This region holds significant growth potential in the green technology sector in the future. The upstream region, comprising Chongqing (0.9260), Sichuan (0.9203), Yunnan (0.8669), and Guizhou (0.7821), has an average GTI efficiency of 0.8738, with overall development constrained by multiple factors. The economic foundation of this region is relatively weak, and traditional agriculture and resource-based industries dominate the industrial structure. Although energy resources are abundant (high energy input), insufficient policy support and weak infrastructure have led to a poor innovation environment. Additionally, the lack of technical talent has resulted in weak demand for green technology R&D and application, ultimately hindering the improvement of GTI efficiency.

4.1.2. Time Dynamics of GTI Efficiency

As an efficiency evaluation index based on relative comparison, the GTI efficiency of provinces and cities in the YREB generally presents a fluctuating feature, and no continuous and stable annual evolution trend is observed. The specific time distribution characteristics are shown in Figure 6.

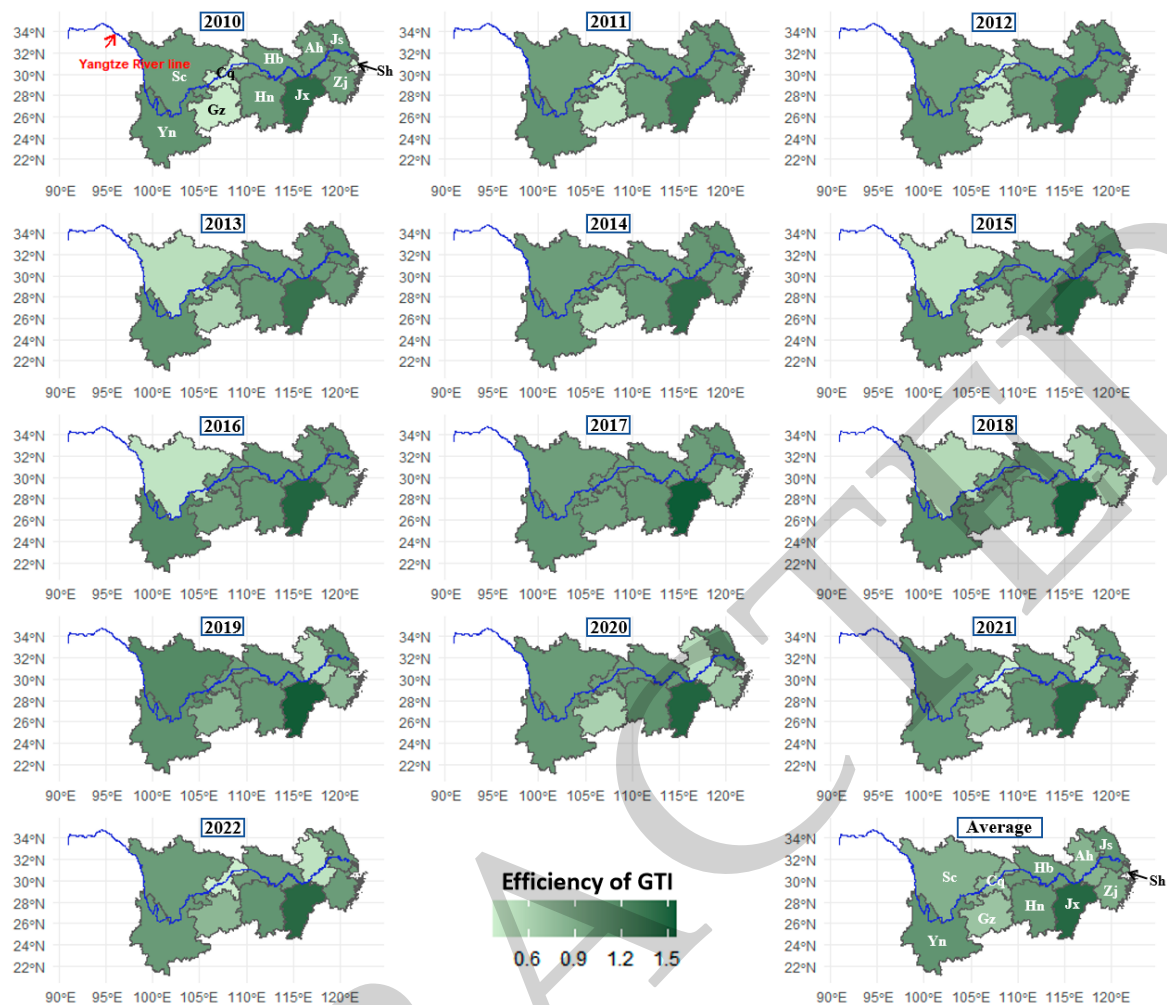


Figure 5. Spatial and temporal changes in GTI efficiency in the YREB.

From the perspective of the downstream, midstream, and upstream regions along the YREB, the GTI efficiency in the downstream region is relatively stable, but still exhibits some fluctuations. Specifically, Shanghai's efficiency is far ahead of the rest of the YREB, fluctuating between 1.3 and 1.6 from 2010 to 2022, with a notable increase between 2013 and 2017, reaching its peak. Zhejiang's efficiency fluctuated between 1.0 and 1.2, showing a relatively stable trend, though it experienced significant fluctuations from 2013 to 2018, followed by a steady decline. Jiangsu's efficiency remained relatively stable, staying between 1.0 and 1.1, slightly lower than Zhejiang's.

The GTI efficiency in the midstream region generally shows a trend of steady increase followed by a decline. Jiangxi maintains a relatively high efficiency, consistently staying above 1.0, and reaching its peak in 2014 before slightly declining thereafter. Hunan's overall performance is relatively stable, with efficiency remaining close to 1.0 for most of the period, experiencing a slight increase in 2016, reaching its peak, and then rapidly returning to near its initial level. Anhui's efficiency remained relatively stable before 2017 but then experienced a significant decline. Hubei recorded the lowest overall efficiency across the entire YREB, with strong volatility throughout the period.

In the downstream region, the GTI efficiency exhibits greater fluctuations. Guizhou shows relatively stable efficiency during the middle period of the study, while Sichuan displays similar stability in the later stages. However, the other provinces and cities in the upstream region experience considerable instability, with frequent and intense fluctuations.

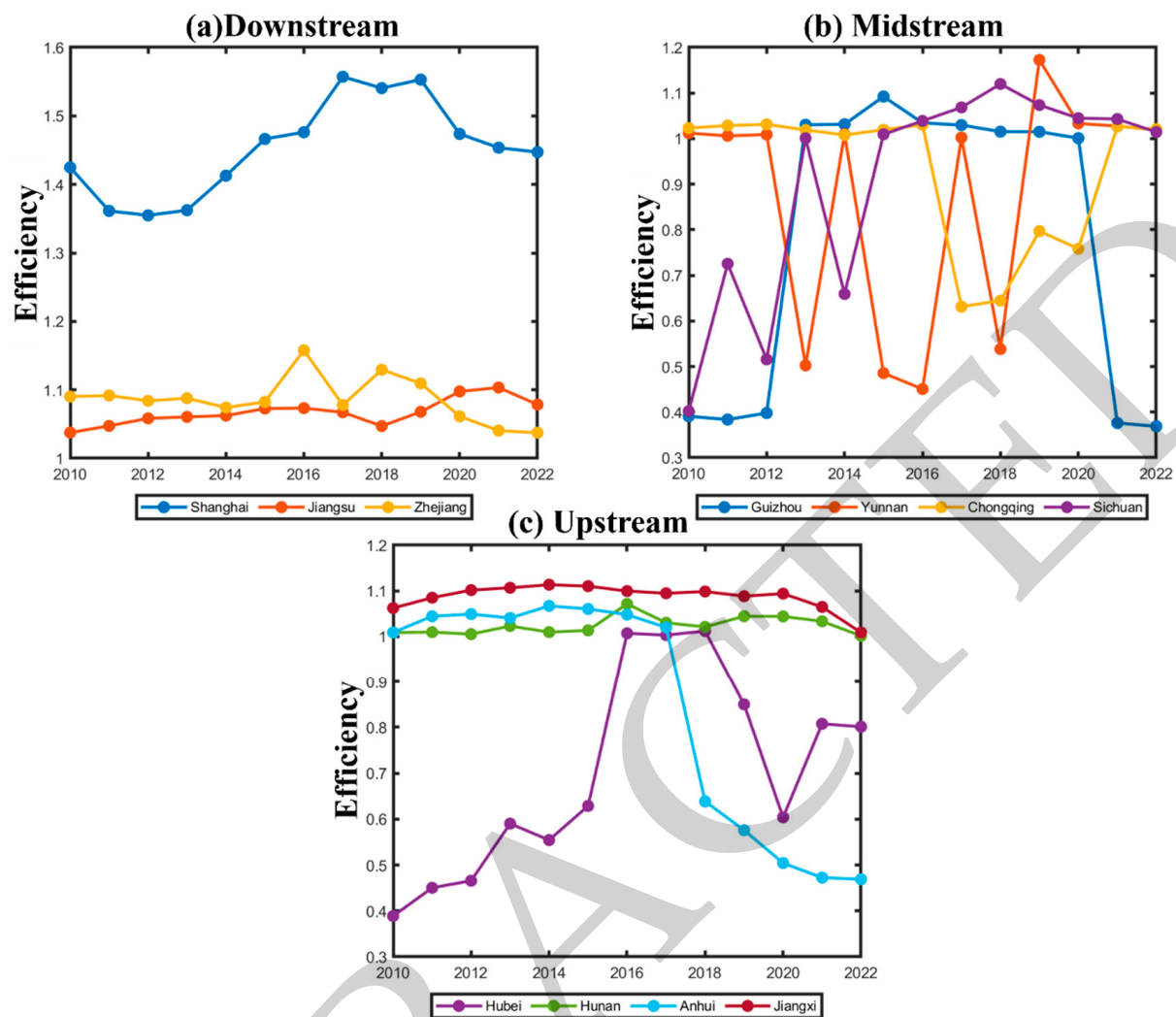


Figure 6. GTI efficiency in the downstream, midstream, and upstream of the YREB. (a) Downstream; (b) Midstream; (c) Upstream.

Overall, the GTI efficiency of the YREB exhibits significant spatiotemporal interaction characteristics. Its temporal evolution can be summarized as a “three-phase differentiated evolution” model. From 2010 to 2016, the region experienced a period of efficiency gradient growth, marked by an overall increase in regional efficiency. From 2017 to 2019, it entered a period of fluctuating adjustment, during which the deepening of supply-side structural reforms led to a structural reallocation of innovation factors across provinces, resulting in considerable efficiency volatility. The COVID-19 pandemic served as a catalyst, significantly accelerating the decline in efficiency observed from 2020 to 2022.

This spatiotemporal interaction pattern indicates that the evolution of GTI efficiency is not only spatially constrained by the maturity of regional innovation systems, but also follows the temporal inertia of technological diffusion.

Furthermore, compared with globally leading regions in green innovation as mentioned in authoritative reports (e.g., the OECD report), such as California, USA (a hub for clean technology and policy innovation), and Japan (leading in resource efficiency and energy-saving technologies), these top-performing regions typically demonstrate significant advantages in R&D intensity, capital investment, and long-term stable environmental policy frameworks [77,78]. Simultaneously, when compared with the downstream regions within the YREB identified in this study as having high GTI efficiency (Shanghai, Jiangsu, Zhejiang), the leading international regions generally exhibit more sustained trajectories of

GTI efficiency improvement and greater resilience to policy fluctuations. This highlights potential gaps in the YREB concerning the stability of its innovation ecosystem and the maturity of its market mechanisms.

4.2. Predicting the GTI Efficiency

4.2.1. Parameter Sensitivity Analysis

To identify the optimal λ and γ minimizing MAPE for GTI efficiency from 2010 to 2020, we conducted Monte Carlo simulations using GM(1,15| λ,γ) in MATLAB 2024a. To verify the robustness of λ and γ , we designed a sensitivity test based on data perturbation, implemented as follows:

Step 1: Generate 100 perturbed datasets by adding $\pm 5\%$ uniformly distributed random errors to the original efficiency values of all regions (2010–2020). Each province's efficiency values were independently perturbed using: Perturbed efficiency value = Original efficiency value $\times (1 + \delta)$, where $\delta \sim U(-0.05, 0.05)$.

Step 2: Retrain the GM(1,N| λ,γ) model on each perturbed dataset. For each experiment, new parameters λ_{new} and γ_{new} were optimized by minimizing MAPE (Formula 12), and the results were recorded.

Step 3: Compute the mean parameter values from the 100 experiments and their relative errors compared to the original parameters. If both parameters' relative errors are below 10%, the robustness test is passed.

The results (Table 4) show that most regions exhibit robust λ and γ values. However, Sichuan and Anhui provinces exceeded the 10% relative error threshold for λ . We posit that this occurs because their original λ values are exceptionally small (0.001 and 0.012, respectively). Since relative error uses the original λ as the denominator, minor absolute changes result in large relative deviations. However, their absolute errors do not vary significantly. Thus, we conclude that GM(1,15| λ,γ) satisfies the robustness criteria.

Table 4. Sensitivity analysis results of parameters.

Regions	λ	λ_{New}	Error (%)	γ	γ_{New}	Error (%)
Shanghai	0.999	0.984	1.502	0.998	1.012	1.403
Jiangxi	1.000	0.947	5.300	1.000	0.973	2.700
Zhejiang	0.995	0.999	0.402	0.987	1.003	1.621
Jiangsu	1.000	0.986	1.400	1.000	0.942	5.800
Hunan	1.000	0.959	4.100	1.000	0.978	2.200
Chongqing	0.894	0.978	9.396	1.021	0.998	2.253
Sichuan	0.001	0.006	600.000	1.190	1.112	6.555
Yunnan	0.879	0.903	2.730	0.756	0.791	4.630
Anhui	0.012	0.039	225.000	0.940	0.971	3.298
Guizhou	1.000	0.937	6.300	1.000	1.074	7.400
Hubei	0.972	0.896	7.819	1.961	1.798	8.312

4.2.2. Prediction Result Analysis

In this section, a detailed analysis of the prediction models for the downstream regions (Shanghai, Jiangsu, Zhejiang) is presented, with a brief analysis of the midstream and upstream regions' prediction results.

The study employs 2010–2022 data to develop GM(1,1), GM(1,15), and GM(1,15| λ,γ) models, segmented into simulation (2010–2020) and prediction (2021–2022) sets for model validation and forecasting analysis. Computational processing was conducted using MATLAB 2024a, with detailed model outputs and error metrics presented in Tables 5–8.

Table 5. Actual and fitted values of GTI efficiency in Shanghai.

Shanghai	Years	Actual	GM(1,1)		GM(1,N)		GM(1,N λ, γ)	
			Fitted	APE (%)	Fitted	APE (%)	Fitted	APE (%)
Simulation	2010	1.4248	1.4248	0	1.4248	0	1.4248	0
	2011	1.3613	1.3574	0.2863	1.397	2.6235	1.3916	2.2279
	2012	1.3548	1.3784	1.7411	1.3775	1.6734	1.3722	1.2842
	2013	1.3623	1.3997	2.7453	1.3701	0.5721	1.3657	0.2464
	2014	1.4127	1.4213	0.6116	1.4161	0.2387	1.4121	0.0394
	2015	1.4664	1.4433	1.5743	1.4685	0.1414	1.4651	0.0899
	2016	1.4762	1.4656	0.7161	1.4766	0.0259	1.4742	0.1325
	2017	1.5572	1.4883	4.4254	1.5598	0.166	1.5576	0.0232
	2018	1.5406	1.5113	1.902	1.5401	0.034	1.5395	0.0746
	2019	1.5531	1.5347	1.1871	1.5535	0.0256	1.5538	0.0457
	2020	1.4737	1.5584	5.7467	1.4712	0.171	1.4737	0.0025
MAPE (%)			1.9033		0.5156		0.3787	
Prediction	2021	1.4536	1.5825	8.8665	1.3896	4.4015	1.3966	3.9222
	2022	1.4472	1.6069	11.0385	1.387	4.1600	1.3918	3.8268
	MAPE (%)		9.9525		4.2807		3.8745	

Table 6. Actual and fitted values of GTI efficiency in Jiangsu.

Jiangsu	Years	Actual	GM(1,1)		GM(1,N)		GM(1,N λ, γ)	
			Fitted	APE (%)	Fitted	APE (%)	Fitted	APE (%)
Simulation	2010	1.0376	1.0376	0	1.0376	0	1.0376	0
	2011	1.0474	1.0528	0.5110	1.0339	1.2843	1.0339	1.2843
	2012	1.0584	1.0556	0.2685	1.0684	0.9482	1.0684	0.9482
	2013	1.0605	1.0584	0.2007	1.0631	0.2462	1.0631	0.2462
	2014	1.0624	1.0612	0.1136	1.0628	0.0393	1.0628	0.0393
	2015	1.0727	1.064	0.8091	1.0724	0.0266	1.0724	0.0266
	2016	1.0733	1.0669	0.6003	1.0733	0.0009	1.0733	0.0009
	2017	1.0673	1.0697	0.2249	1.0675	0.0199	1.0675	0.0199
	2018	1.0471	1.0726	2.4307	1.0478	0.0678	1.0478	0.0678
	2019	1.0679	1.0754	0.7033	1.0672	0.0684	1.0672	0.0684
	2020	1.0977	1.0783	1.7694	1.0967	0.0954	1.0967	0.0954
MAPE (%)			0.6938		0.2543		0.2543	
Prediction	2021	1.1034	1.0812	2.0164	1.1432	3.6070	1.1432	3.6070
	2022	1.0785	1.0840	0.5130	1.0294	4.5549	1.0294	4.5549
	MAPE (%)		1.2467		4.0810		4.0810	

For the three downstream cities, the model parameters for Shanghai, Jiangsu, and Zhejiang are as follows: parameters for Shanghai are $\lambda = 0.999, \gamma = 0.998$, parameters for Jiangsu are $\lambda = 1.000, \gamma = 1.000$, and parameters for Zhejiang are $\lambda = 0.995, \gamma = 0.987$. Among the three cities, the model errors, evaluated using the MAPE criterion, are as follows: Shanghai: 3.1416%, 1.0948%, 0.9165%; Jiangsu: 0.7816%, 0.8430%, 0.8430%; Zhejiang: 2.3865%, 2.3042%, 1.6842%. Compared to the univariate GM(1,1) model, the GM(1,N) models not only handle the primary variable, but also consider the relationships between multiple influencing variables, making the error sources more complex. Additionally, the GM(1,N) models require higher data quality and relevance, which makes direct comparisons difficult. However, the GM(1,15 | λ, γ) model performs better than the first two models in terms of MAPE in most provinces and cities (except Jiangsu). This phenomenon primarily arises from the concurrent adjustment of both the 1-AGO sequence and the background value sequence by parameters λ and γ . This dual-parameter correction mechanism is cen-

tral to the model's classification as dual dynamic. Theoretically, under the dual correction, the GM(1,15| λ,γ) model should provide the best predictive performance because the λ parameter dynamically adjusts the accumulated generation operator (1-AGO) sequence, while the γ parameter corrects the background values. This dual correction enables the model to more accurately reflect the intrinsic patterns of data variation, improving the model's adaptability to complex systems and resulting in higher accuracy in predictions. This instance also confirms this theory.

Table 7. Actual and fitted values of GTI efficiency in Zhejiang.

Zhejiang	Years	Actual	GM(1,1)		GM(1,N)		GM(1,N λ,γ)	
			Fitted	APE (%)	Fitted	APE (%)	Fitted	APE (%)
Simulation	2010	1.0902	1.0902	0	1.0902	0	1.0902	0
	2011	1.0918	1.0902	0.1426	0.9726	10.9134	0.9717	10.9982
	2012	1.084	1.0914	0.6857	1.0864	0.2213	1.0845	0.0435
	2013	1.0878	1.0926	0.4434	1.087	0.0702	1.0847	0.2878
	2014	1.0742	1.0938	1.8260	1.0771	0.2716	1.0745	0.0241
	2015	1.0824	1.095	1.1648	1.0806	0.1624	1.0777	0.4304
	2016	1.1578	1.0962	5.3203	1.1416	1.396	1.1384	1.6765
	2017	1.0779	1.0974	1.8088	1.095	1.589	1.0917	1.2779
	2018	1.1294	1.0986	2.7276	1.1184	0.9775	1.1148	1.2886
	2019	1.1095	1.0998	0.8749	1.1138	0.3845	1.1101	0.0539
	2020	1.0613	1.101	3.7399	1.0716	0.9735	1.068	0.6288
	MAPE (%)		1.7031		1.5418		1.5191	
Prediction	2021	1.0405	1.1022	5.9292	1.145	10.0393	1.0613	1.9998
	2022	1.0374	1.1034	6.3616	1.0681	2.9559	1.0044	3.1847
	MAPE (%)		6.1454		6.4976		2.5923	

Table 8. Actual and fitted values of GTI efficiency in the remaining regions of the YREB.

		GM(1,1)	GM(1,N)	GM(1,N λ,γ)
Jiangxi	Simulation	0.5189	0.4534	0.4534
	Prediction	5.6712	3.8865	3.8865
Hunan	Simulation	0.9113	0.8001	0.8001
	Prediction	3.4865	2.7579	2.7579
Sichuan	Simulation	13.0805	6.2878	5.8352
	Prediction	21.1672	4.3241	4.0716
Guizhou	Simulation	23.2815	5.7612	5.7612
	Prediction	237.5878	59.7805	59.7805
Anhui	Simulation	12.9514	4.2272	3.1393
	Prediction	17.0766	10.1731	9.2925
Yunnan	Simulation	35.6197	24.619	23.8977
	Prediction	14.1961	8.3742	6.6339
Chongqing	Simulation	9.6739	2.5382	2.5233
	Prediction	36.7802	14.9648	10.7813
Hubei	Simulation	16.7367	12.6257	11.9624
	Prediction	24.9774	16.3928	11.8653

However, in Jiangsu, the GM(1,15) model already achieved excellent predictive performance, and thus, within the parameter range, the GM(1,15| λ,γ) model performed best when it coincidentally matched the GM(1,15) model, which also suggests that the GM(1,15| λ,γ) model provides the best predictive results. In addition, for the Jiangsu case, the observed higher prediction error in multivariate models (GM(1, N) and GM(1, N | λ,γ)) compared to the univariate model (GM(1,1)) can be attributed to the susceptibility

of their multi-variable interaction structure to transitory variations. Specifically, when regional GTI efficiency demonstrates strong temporal autocorrelation (as seen in Jiangsu's minimal efficiency fluctuations during 2010–2020) and the influencing factor variables (e.g., green bonds) exhibit short-term anomalies, the multivariate frameworks tend to introduce amplified noise propagation, consequently increasing extrapolation bias. This outcome is unique to the Jiangsu scenario and represents a region-specific occurrence.

Analysis of error sources indicates that GTI efficiency, being a composite metric, exhibits complex trends rather than simple patterns (Figure 7). Notably, Zhejiang's data display abrupt shifts around 2016 and 2018, identified as outliers. These outliers contribute to the variations in simulation accuracy observed across the three models. Furthermore, the limited dataset magnifies the impact of outliers on error in specific models, as Figure 8 demonstrates. Among the models tested, GM(1,15| λ,γ) achieved the lowest prediction error. This performance advantage stems from its adherence to the new information principle. Through iterative parameter tuning guided by trend correction, the model successively reduces prediction error, surpassing both the standard GM(1,15) and GM(1,1) models.

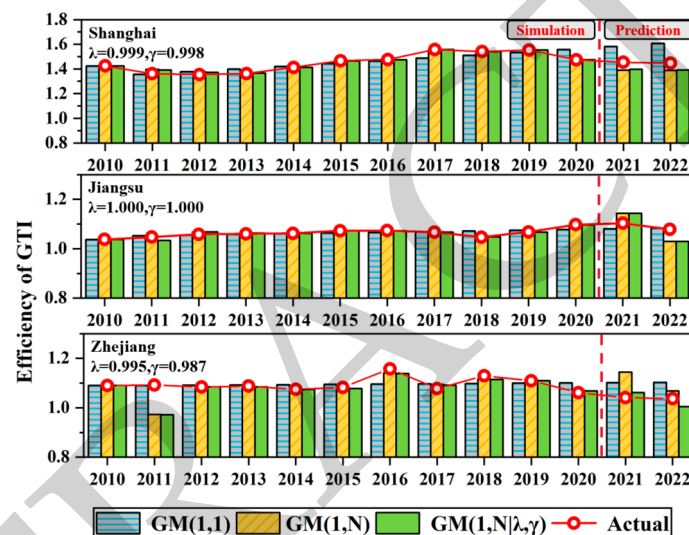


Figure 7. Actual values and fitted values of the three models (downstream).

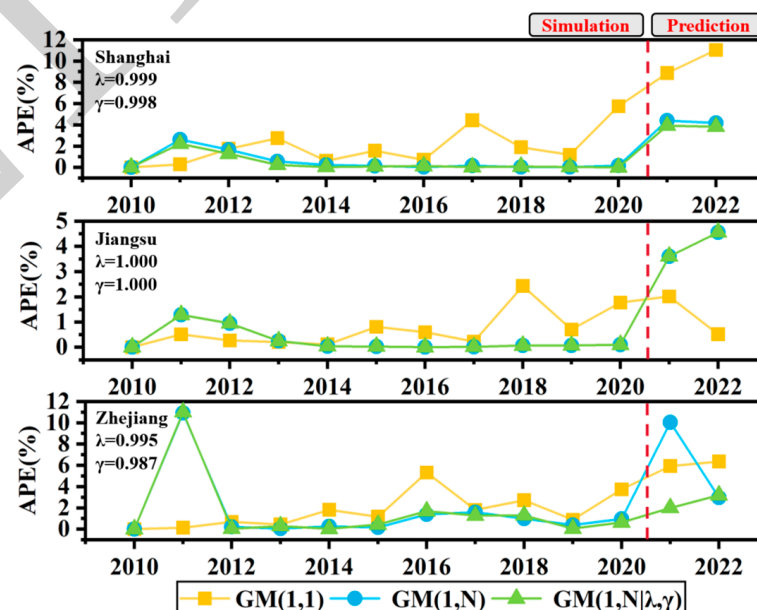


Figure 8. APE for three models (downstream).

The results of the three models for cities in the middle and upper regions are shown in Table 8. It is evident that the $GM(1,15|\lambda,\gamma)$ model outperforms the $GM(1,1)$ model and the $GM(1,15)$ model in terms of accuracy. Therefore, the $GM(1,15|\lambda,\gamma)$ model is used in the subsequent regional difference analysis.

Figure 9 presents the real values, fitted values, and APE (Absolute Percentage Error) changes from 2010 to 2022 in the form of a radar chart. Taking APE as an example, the error decreases as it moves from the center to the outer circle. The closer to the center, the smaller the error. It is clear that the fitted values for all regions generally follow the same trend as the real values. Downstream GTI efficiency consistently surpasses that of both upstream and midstream regions every year. Similarly, while midstream efficiency exceeds upstream levels in most years, it does not consistently outperform the downstream region.

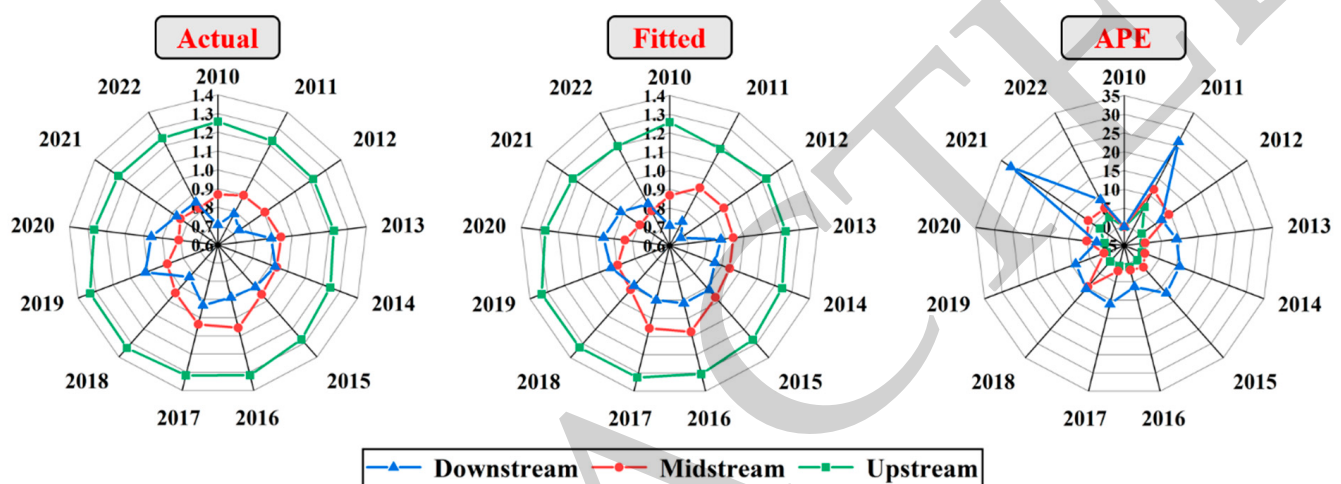


Figure 9. Changes in actual, fitted values, and APE in the upstream, midstream, and downstream of the YREB.

The predicting accuracy of the YREB also shows significant regional differences. Overall, all three regions experienced considerable errors in 2011, which can be attributed to the poor performance of the $GM(1,N|\lambda,\gamma)$ model in extracting new information when only a single data point is available, leading to larger errors. From a regional perspective, the downstream region, benefiting from a strong economic foundation and policy support, has consistently maintained a leading and stable GTI efficiency. This has allowed the predicting model to more accurately capture its development trend, resulting in better model fitting and relatively smaller prediction errors. In the middle region, the GTI efficiency shows a trend of first increasing and then decreasing. The errors exhibit a cyclical pattern of first increasing and then decreasing, with significant errors not only in 2011, but also in 2018. In 2018, the manufacturing industry in the middle region had a single industrial structure, heavily reliant on traditional, high-pollution, and high-energy-consuming industries. As a result, China implemented a series of policies to prevent further deterioration, which led to stronger environmental regulations and caused larger errors during model fitting. Although the upstream region has great development potential, its economic and technological foundation cannot fully support its development, resulting in a highly volatile GTI efficiency. This fluctuation causes the predicting model to fail in compensating for the loss caused by outliers after extracting new information, ultimately leading to increased errors.

Theoretically, the dynamic evolutionary process of GTI is not merely a technological accumulation, but manifests as a complex systemic process involving multidimensional interactions among resource inputs, environmental policies, market responses, and other factors. This process can be attributed to the “green innovation diffusion theory,” which

emphasizes the absorption, diffusion, and rebalancing mechanisms of innovation within regions. This study constructs an “input-desirable output-undesirable output” framework and employs the SBM model to quantify GTI efficiency, essentially capturing a static representation of innovation diffusion mechanisms. Meanwhile, the introduction of the $GM(1,N|\lambda,\gamma)$ model enables us to unveil the temporal dynamic evolutionary trajectory of these mechanisms. Notably, the λ parameter reveals the novel information effect of policy shocks, while the γ parameter embodies nonlinear diffusion effects, collectively reflecting the adaptability of the GTI system when confronting environmental fluctuations. This research not only fills a theoretical gap in understanding the dynamic evolution of GTI efficiency, but also provides a theoretical toolkit for comprehending regional green low-carbon transition mechanisms, offering a scholarly foundation for optimizing green innovation policies.

5. Conclusions and Policy Implications

Confronted with intensifying climate and resource constraints, China's YREB, spanning 11 critical regions, faces urgent pressure to advance sustainable consumption patterns. To address manufacturing's high energy intensity and pollution in this corridor, this study employs the joint SBM and super-efficiency SBM model to quantitatively evaluate GTI efficiency. The analysis incorporates inputs, desirable outputs, and undesirable outputs. Additionally, the study innovatively incorporates parameters λ and γ to optimize the multivariate grey $GM(1,N)$ model, combining factors such as environmental regulation, green finance, and government policies for predictive analysis.

5.1. Conclusions

Analysis utilizing this integrated model demonstrates its efficacy not only in delineating the regionally heterogeneous characteristics of green development within the manufacturing sectors across the upstream, midstream, and downstream of the YREB, but also in significantly bolstering the robustness of predictive outcomes through algorithmic enhancements. The principal findings of this study are as follows:

(1) The joint evaluation model utilizing the SBM and Super-SBM models indicates that the overall level of GTI efficiency in the manufacturing sector of the YREB was relatively low between 2010 and 2020. The average efficiency rankings were as follows, Shanghai (1.4526), Jiangxi (1.0870), Zhejiang (1.0865), Jiangsu (1.0672), Hunan (1.0245), Chongqing (0.9260), Sichuan (0.9203), Yunnan (0.8669), Anhui (0.8426), Guizhou (0.7821), and Hubei (0.7049), revealing significant regional heterogeneity. Temporally, GTI efficiency peaked around 2016 in nearly all provinces and cities. This aligns with the findings of Tang et al. (2020), who observed that the effect of environmental regulations in driving increased green innovation investment among Chinese industrial enterprises became evident during the later stage of the 12th Five-Year Plan (approximately 2013–2015). This timing likely reflects the lagged manifestation of accumulated policy effects. However, significant fluctuations in efficiency around 2020 differ from the conclusions reached by scholars like Yao et al. [79]. As the experimental results are comparative data, and this study uniquely incorporates data from 2021 and 2022, some divergence is reasonable. This study attributes this phenomenon to disruptions in regional innovation systems caused by the external shock of 2020 (e.g., the pandemic) and policy transitions (e.g., the accelerated “dual-carbon” goals). By dynamically tracking annual efficiency values, this study provides a more intuitive revelation of the immediate and short-term impacts of such major events on GTI efficiency.

(2) Analysis of the GTI efficiency evaluation results indicates that from 2010 to 2020, the average GTI efficiency of the downstream regions (Shanghai, Jiangsu, Zhejiang), mid-stream regions (Jiangxi, Hunan, Anhui, Hubei), and upstream regions (Guizhou, Sichuan,

Yunnan, Chongqing) was 1.2021, 0.9148, and 0.8738, respectively (downstream > midstream > upstream). This finding aligns with the conclusions of Wang et al. [24] and Yao et al. [80], both demonstrating a significant east-high-west-low gradient difference in GTI efficiency across the YREB. Compared to the downstream regions, the midstream regions suffer from insufficient input, while the upstream regions face even more limited input. Coupled with inadequate environmental governance capacity, this results in a high ratio of undesirable outputs to inputs, leading to suboptimal efficiency. This also reflects the substantial potential for improving GTI efficiency and promoting manufacturing development in the midstream and upstream regions. This provides regional-level empirical evidence for Sharif et al.'s (2023) view that green technology innovation requires systematic resource support, and it also echoes Liu et al.'s [69] assertion regarding the impact of environmental governance capacity on efficiency.

(3) Unlike Wu et al. [13], who proposed the new information adjustment parameter and the nonlinear background parameter that primarily held theoretical significance, this study further establishes the practical value of these two parameters. Significant inter-provincial differences exist in the effectiveness of both the new information adjustment parameter and the nonlinear background parameter for predicting GTI efficiency. Downstream regions exhibit γ values close to 1, indicating lower path dependency and mature adoption of green technologies. In contrast, midstream and upstream regions (e.g., Hubei, Sichuan) show γ values significantly deviating from 1, reflecting severe technology lock-in and dependence on traditional energy sources. This signals that they face more formidable challenges in overcoming transition lock-in, a finding that resonates at the regional level with Li and Xiao's [15] discovery regarding the heterogeneous impact of environmental regulations on corporate green innovation across industries (notably greater inhibition in capital-intensive industries). Furthermore, some midstream and downstream regions (e.g., Sichuan, Anhui) exhibit extremely low λ values, suggesting rapid policy responsiveness. However, this also implies potential efficiency fluctuations due to frequent policy changes. This validates Howlett's [72] policy iteration theory concerning the varying speeds of policy feedback loops across regions and explains why frequent policy adjustments can lead to efficiency volatility [46]. These insights are crucial for understanding the differential effectiveness of policy transmission across regions.

(4) This paper uses three models—GM(1,1), GM(1,N), and GM(1,N| λ,γ)—to predict GTI efficiency. Compared to the first two traditional models, the GM(1,N| λ,γ) model proposed in this study achieves the highest accuracy. It provides better fitting results for the GTI efficiency of different regions and development trends. This is mainly because of the significant “poor-information, grey-characteristic” of GTI. The new information adjustment parameter λ and the non-linear background parameter γ emphasize the role of new information, better extracting the hidden trends from new information.

5.2. Policy Implications

This study reveals significant regional gradient disparities (downstream > midstream > upstream) and periodic fluctuation characteristics in the GTI efficiency of manufacturing industries along the Yangtze River Economic Belt. Based on model evaluation and prediction results, the following recommendations are proposed:

(1) Strengthening Collaborative Innovation Elements in Midstream and Upstream Regions: Research findings indicate that the GTI efficiency in midstream and upstream regions is constrained by insufficient R&D investment, high energy dependence, and technological path lock-in. To address these issues while aligning with sustainability goals, policymakers should leverage the “regional innovation resource-sharing” mechanism proposed in the Yangtze River Economic Belt Development Plan to establish cross-provincial

platforms for sharing green innovation elements, promoting cross-provincial mobility of scientific talent and collaborative R&D. For instance, targeting Guizhou province, which exhibits low efficiency, a priority could be placed on establishing green technology transfer platforms connecting universities, research institutes, and local manufacturing enterprises. Leveraging its big data infrastructure advantages, a regional green patent and technology database could be developed to lower barriers to technology access.

(2) Building a Policy Resilience Evaluation Mechanism: Studies reveal that frequent policy adjustments (e.g., the accelerated carbon neutrality targets in 2020) and external shocks (e.g., the pandemic) have caused drastic fluctuations in efficiency. Guided by the “dynamic adaptive policy framework” outlined in the *14th Five-Year Plan for Climate Change Response*, a “warning-feedback-calibration” mechanism should be established. On one hand, the improved $GM(1,N|\lambda,\gamma)$ model could be applied to predict potential policy-driven efficiency fluctuations, enabling preemptive risk identification. On the other hand, transitional policy instruments should be designed in line with the *National Emergency Response System Construction Plan* to avoid abrupt disruptions to innovation chains caused by “sudden brakes.”

(3) Integrating Predictive Models into Decision-Making Systems: The enhanced $GM(1,N|\lambda,\gamma)$ model demonstrates superior prediction accuracy and policy interpretability compared to traditional models. Implementing the requirements for “intelligent decision support systems” in the *New Generation Artificial Intelligence Development Plan*, a dynamic monitoring platform for green innovation in the YREB should be developed, integrating model parameters with real-time data. For instance, downstream provinces with $\gamma \approx 1$ (e.g., Shanghai) should prioritize support for cutting-edge technology commercialization, while midstream regions with γ deviating from 1 (e.g., Hubei) should focus on digital and low-carbon transformation of traditional industries. Furthermore, referencing the *Dual Carbon Standardization Enhancement Action Plan*, model predictions should be incorporated into provincial carbon emission assessment systems to enhance the scientific rigor and differentiation of five-year planning targets.

5.3. Research Deficiencies and Prospects

This study has certain limitations. For example, dynamic efficiency analysis (such as the Malmquist index) has not been incorporated. Could this reveal whether the nature of efficiency changes is driven by technological progress or scale effects? Does the policy cycle have a phased driving effect on GTI? By evaluating the efficiency of the manufacturing industry as a whole, does this overlook the technological heterogeneity between high-energy-consuming industries (such as steel and chemicals) and low-pollution industries (such as electronics and information technology)? How can destructive effects such as COVID-19 be directly introduced into the prediction model? These issues provide new directions for expanding this research.

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