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Eco-Efficiency Evolution of Water-Intensive Polluters in the Yangtze River Economic Belt: A Spatial-Temporal Analysis Using the DEA-Malmquist Index

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ABSTRACT

Occupying a preeminent position as the globe's most extensive economic corridor, the Yangtze River Economic Belt (YREB) serves as a crucial aquifer for 800 million individuals and harbors almost 50% of the country's paramount water-intensive contaminant producers. The ecological efficiency of these producers within the belt has increasingly come under scholarly scrutiny. Leveraging data from 2004-2012 encompassing 725 such manufacturers and employing the DEA-Malmquist index methodology, this research delineates the eco-efficiency trajectories of these water-centric pollutant producers, shedding light on their spatial-temporal dynamics across the expansive Yangtze Economic Belt. The results are as follows: (1) there's a discernible enhancement in the eco-efficiency (*ML*) of these manufacturers situated within the YREB, predominantly propelled by technological change (*TC*) and shifts in technical efficiency change (*TEC*); (2) From a spatial perspective, notable disparities emerge in both technological change (*TC*) and technical efficiency change (*TEC*) among the belt's upper, middle, and lower tiers. Intriguingly, the hierarchy for *TC* and *TEC* descends as follows: Lower > Upper > Middle; (3) Examining the spatial evolution nuances, 2004 witnessed eco-efficiency distributions ranking from Upper > Middle > Lower. Fast forward to 2012, a marked reconfiguration appears with a distribution pattern of Middle > Lower > Upper.

KEYWORDS

Eco-efficiency; Yangtze River Economic Belt; National Key Pollution Monitoring Enterprises; Malmquist Index; Spatial-Temporal Analysis

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1. Introduction

The Yangtze River Economic Belt (YREB) holds a crucial position in China's economy and ecology. As the industrial and economic center of China, this region contributes nearly 50% of the national GDP, houses about 40% of the population, and accounts for approximately 60% of the country's import and export trade (Zhou et al., 2021). However, this economic hub also faces severe environmental challenges. The latest data shows that the YREB's discharge of polluted water accounts for more than 40% of the national total, which serves as a vital drinking water source for 800 million people. Therefore, balancing rapid economic development with water environmental protection has become a major concern for both the Chinese government and the international community.

Although numerous studies have explored methods to improve the production efficiency of water-intensive polluting enterprises (Zhao et al., 2024; Huang et al., 2023; Su et al., 2023), these studies often focus on traditional Total Factor Productivity (TFP) analysis, neglecting eco-efficiency, which better integrates economic growth with environmental protection. Eco-efficiency takes into account environmental effect elements in addition to economic production, and it has been increasingly applied in green development studies in recent years (Fan et al., 2019). Thus, the goal of this study is to provide a scientific basis for sustainable regional development by analyzing the spatio-temporal changes in the water-intensive, polluting businesses' green production efficiency in the YREB. Using complex firm-level data and the DEA-Malmquist index method, this paper conducts a thorough evaluation of the effectiveness of green production and its spatio-temporal evolution in water-intensive polluting enterprises in the YREB. The research includes evaluating green production efficiency and its temporal changes, analyzing regional differences in green production efficiency and their causes. We want to provide theoretical support for the synchronized growth of the environment and economics in this region by revealing the state and trends of green production efficiency in the YREB through these analyses.

This study makes significant contributions and innovations in several aspects. Firstly, it is the first to use data at the level of water-intensive polluting firms on the YREB from 2004-2012 to provide a characterisation of the spatio-temporal evolution of the eco-efficiency of these firms on the YREB. Second, it reveals the reasons for the increase in productivity of pollution-intensive firms in terms of technology and technical efficiency. Third, plenty of research has been conducted to evaluate the eco-efficiency of firms, but there is still a gap in research on the evolution of technology and technical efficiency. This study not only provides empirical analyses for the development of corporate eco-efficiency in China in the YREB, but also provides strong support for technological change in other countries and regions.

The rest of the paper proceeds as follows. Section 2 offers a literature review. The data and model are described in Section 3. In Section 4, the estimation findings will be discussed. The YREB's ecological efficiency's chronological and spatial evolution is covered in Section 5, and the findings are presented in the last section.

2. Literature Review

Within the prevailing academic corpus, research on eco-efficiency gravitates around three seminal themes. Initially, scholars endeavor to discern the determinants of industrial eco-efficiency, subsequently proffering recommendations to attenuate pollution in manufacturing sectors. From a historical perspective, examinations of the spatial-temporal metamorphosis of eco-efficiency predominantly spotlight industrial agglomeration. This is principally accomplished through meticulous delineations of regional variations, underscoring the spatial-temporal dichotomies in eco-efficiency. Lastly, a fervent discourse has burgeoned around the ramifications of environmental regulation on eco-efficiency.

2.1. Eco-efficiency of specific industries

Eco-efficiency of industrial is an essential part of eco-efficiency, especially in industrial manufacturing. From 2005 to 2015, Matsumoto and Chen (2021) examined the industrial eco-efficiency of thirty Chinese provinces, followed by an analysis of the factors influencing eco-efficiency. Liu et al. (2020) use a panel tobit regression model to investigate the effect of industrial policy on the eco-efficiency of the industrial division using panel data from the Chinese industrial sector. They generally agree that the overall eco-efficiency of our industry has steadily improved, largely due to *TC*. In addition, increased investment in environmental protection and high-quality services is also a catalyst for eco-efficiency. In developed countries, the industrial economy is growing rapidly, the economic structure is sluggish, and energy consumption is high. All these factors reduce the efficiency of the industrial economy. Technology services, financial services, logistics services, and other related areas have been studied extensively regarding TFP. In accordance with the theories of production, innovation, and competition, Wang (2023) investigates how rural human capital inputs affect total farm productivity. Radicic et al. (2023) propose that the pace of TFP growth, or the convergence process, increases with a country's distance from the frontier in the financial services sector of Central and Eastern Europe (CEE) countries.

In terms of the manufacturing industry's ecological efficiency, Zhang and Liu (2021) assessed the environmental performance of commercial businesses using an undesired output model (S-DEA-SBM-UO) based on Super Data Envelopment Analysis and Relaxation Metrics, which proposed countermeasures and recommendations for industrial pollution control. Li and Winter (2012) present an eco-efficiency method to assess how resource- and energy-efficient manufacturing operations are and propose strategies to improve the eco-efficiency of manufacturing processes according to the analysis. Similarly, Simboli et al. (2014) discuss the potential synergies of integrating industrial eco-methods and tools in manufacturing to improve eco-efficiency by introducing environmental loads as another type of Muda. Based on this fact, Wang et al. (2023) address that artificial intelligence can contribute to improving eco-efficiency.

2.2. Spatial and temporal variation in eco-efficiency

Regarding the temporal and spatial differentiation of eco-efficiency, the literature emphasizes industrial agglomeration's effect on eco-efficiency, grouped by different regions. Most scientists divide the area into a single small region to study the characteristics of the deep divergence within a particular region. Liu et al. (2020) utilize Chinese province-level panel data spanning the years 1978 to 2017 to examine the spatial features of China's agriculture eco-efficiency. Again, the growth of agricultural eco-efficiency in China at the provincial level is characterized by regional imbalances, polarization, differentiation, agglomeration, and restructuring over the same time period. As part of China's agricultural economy as a whole, the distribution of agro-ecological efficiency across the nation has also been examined in some studies. Liao et al. (2021) investigate the spatial distribution pattern of agroecological efficiency in China using a spatial autocorrelation technique. Habib et al. (2021) analysis ascertains movement between COVID-19, crude oil prices, and atmospheric CO_2 emissions over frequency and time domain. Utilizing an intermediary impact framework constructed from data panels from 287 Chinese cities and a regionally variable panels Durbin model between 2003 and 2016, a study by Yuan et al. (2020) explores the nonlinear industrialization agglomeration's effects on ecological efficiency and its impact channels. According to Zhao et al. (2022), a new super-efficient Data Envelope Analysis (DEA) was developed for global SBM at the meta-boundary. According to Zhao et al. (2022), China has achieved superior green economic growth between 2003 and 2018, with the most significant improvements in the northeastern and eastern coastal cities. Their spatio-temporal development characteristics and intrinsic influence mechanisms have been studied.

2.3. Environmental efficiency impact of government regulation

Numerous studies have been conducted on the effect of government regulation on eco-efficiency, but no consensus has been reached. Tian and Feng (2021) discuss environmental rules' effects on eco-efficiency, finding that as government environmental regulation increases, eco-efficiency tends to decrease. In a similar study, Li et al. (2023) found that TFP benefits from environmental legislation, and the degree of impact is different in different regions. To further explain the mechanism of environmental regulation, Clò et al. (2016) analyze the nonlinear link between production efficiency and environmental control, concluding that technological and structural effects account for the largest impact of environmental regulation. Regarding the indirect effects of opening a government to foreign investment, Poelhekke and Ploeg (2015) suppose that cross-border investment can transform and improve domestic firms' environmental management models through intra-industry demonstration effects, as well as upstream and downstream industry convergence, thereby improving a country's eco-efficiency.

Using the synergistic mechanism of industrial agglomeration, Zhang et al. (2019) study the impact of environmental regulations on pollution, the result shows that environmental regulations not only increase industrial agglomeration but also significantly worsen pollution across the country. Ren et al. (2019) claim that foreign direct investment from openness significantly inhibits eco-efficiency gains.

Similar forms of research exist in many other sectors. According to the findings, the eco-efficiency of agriculture and industry has significant variability in its spatial and temporal distribution, and both are related to the temporal and spatial agglomeration of enterprises in a given area. Environmental protection and economic development can be better understood through all these studies.

3. Model and Data

3.1. Model

In contemporary academic discourse, the DEA-Malmquist index model emerges as a salient non-parametric paradigm, adept at gauging the temporal progression of TFP (Zheng, 2021). The DEA methodology does not circumscribe the quantity of output variables, thus accommodating a multifaceted interplay of both input and output dimensions (Ding et al., 2023; Ding et al., 2022). This study employs the Malmquist index, anchored in DEA, to discern shifts in eco-efficiency trajectories. Subsequently, it decomposes these shifts into alterations in technology and variances in technical efficiency, offering an incisive exploration into the wellsprings of eco-efficiency augmentation.

Within the sophisticated tapestry of academic inquiry, the Malmquist index is delineated via distance functions, encompassing both input and output dimensions. First, we assume that for input $X\in R^{N+}$, Output $Y\in R^{M+}$, the set of production possibilities S^t at moment t can be defined as:

$$S^t = \{((x,y)|In\ period\ t, X\ produces\ Y)\} \tag{1}$$

Where S^t represents the amalgamation of all input-output combinations of at time *t.*

Referring to Shephard (1970), the distance function for output is defined on the production possibility set. The distance function is as follows:

$$D_i^t(X^t,Y^t) = inf\{\theta|(X^t,Y^t/\theta\epsilon S^t)\} = (sup\{\theta(X^t,Y^t\theta\epsilon S^t)\})^{-1} \tag{2}$$

Where the subscript *i* indicates that the distance function based on output.

When the entire economic system is encapsulated within the production process, the production frontier is derived, and then a distance function for different periods is used to calculate the distance between each production unit and the production frontier. By the definition $D_i^t(X^t,Y^t) \le 1$ is equivalent to $(X^t,Y^t) \in$

S^t.When $D_i^{t+1}(X^t, Y^t) = 1$, (X^t, Y^t) is the point on the production frontier, i.e. production is technically the most efficient in terms of maximum output. And the distance function $D_i^t(X^{t+1}, Y^{t+1})$ involving two different moments represents the ratio of the maximum possible output and the time output that (X^{t+1}, Y^{t+1}) can achieve at time *t*, i.e. :

$$D_i^t(X^{t+1}, Y^{t+1}) = inf\left\{\theta: \left(X^{t+1}, \frac{Y^{t+1}}{\theta}\right) \in S^t\right\} \tag{3}$$

Thus, the output-based Malmquist function at time *t* can be defined as:

$$\mathrm{M_i^t} = \frac{\mathrm{D_i^t(X^{t+1},Y^{t+1})}}{\mathrm{D_i^t(X^t,Y^t)}} \tag{4}$$

Similarly, $D_i^{t+1}(X^t, Y^t)$represents the ratio of the maximum possible and temporal output that (X^t, Y^t) can achieve at the level of technology at time *t+1*, so the Malmquist function at time *t+1* can be defined as:

$$\mathrm{M_i^{t+1}} = \frac{\mathrm{D_i^{t+1}(X^{t+1},Y^{t+1})}}{\mathrm{D_t^{t+1}(X^t,Y^t)}} \tag{5}$$

Based on Fisher's (1922) idea of an ideal index, changes in eco-efficiency can be calculated using a geometric mean based on the Malmquist index at time t and t+1.

$$\begin{aligned}\mathrm{ML}(X^t, Y^t, X^{t+1}, Y^{t+1}) &= \left[\frac{D_i^t(X^{t+1}, Y^{t+1})}{D_i^t(X^t, Y^t)} \times \frac{D_i^{t+1}(X^{t+1}, Y^{t+1})}{D_i^{t+1}(X^t, Y^t)}\right]^{\frac{1}{2}} \\ &= TC(X^{t+1}, Y^{t+1}) \times EC(X^{t+1}, Y^{t+1})\end{aligned} \tag{6}$$

The model includes three indices: *ML*, *TC*, and *EC*. The index *ML* represents eco-efficiency, and the decomposition of *ML* gives technological change (*TC)* and technical efficiency change (*TEC)*.

In the above equation, for each observed sample, a value of *ML* greater (less) than 1 indicates an increase (decrease) in TFP from *t* to *t+1*; a value of *TC* greater (less) than 1 indicates technological progress (regress) from *t* to *t+1*; and a value of *EC* greater (less) than 1 indicates an improvement (regress) in *TEC* from *t* to *t+1*. *TC* refers to the contribution of independent innovation or technology adoption to industrial production. Improvements in *TEC* indicate that reform of the system has improved the efficiency of resource allocation, leading to higher levels of industrial productivity.

Specifically, to measure the index *ML* for province *K* at time *t* as base period *t+1*, the ratio of the maximum possible output and the temporal output that can be achieved with different technology levels at different times needs to be solved: $D_k^t(X^t, Y^t)$, $D_k^{t+1}(X^t, Y^t)$, $D_k^t(X^{t+1}, Y^{t+1})$ and $D_k^{t+1}(X^{t+1}, Y^{t+1})$. Of which, the linear programming expression for $D_k^t(X^t, Y^t)$ is as follows:

$$[D_k^t(X_k^t, Y_k^t)]^{-1} = max\theta^k$$

$$\mathrm{s.t.}\, \theta^k Y_k^T, m \le \textstyle\sum_{k=1}^k Z_k^t Y_k^t, m \quad m = 1,2, \dots, M$$

$$\sum_{k=1}^k Z_k^t Y_k^t, n \le X_k^t, n \quad n = 1,2, \dots, N$$

$$Z_k^t \ge 0 \quad k = 1,2, \dots, K \tag{7}$$

And so on, the linear programming expressions for $D_k^{t+1}(X^t, Y^t)$, $D_k^t(X^{t+1}, Y^{t+1})$ and $D_k^{t+1}(X^{t+1}, Y^{t+1})$ can be obtained, and then solved using equation 6 to obtain the *ML* index.

3.2. Data source

3.2.1. Permission to reuse and Copyright

Water-intensive polluting businesses from the Environmental Survey and Report (ESR) serve as the study's main source of data, which is administered by the Environmental Protection Ministry. China began gathering data on industrial pollutants' effects on the environment and wastes in the 1980s. The main function of the purpose of ESR is to gather data on main pollution sources, including the name, industry, whereabouts and resultant value of the emitter, and covers heavily polluting industrial enterprises, hospitals, domestic sewage treatment plants, facilities for treating hazardous waste, and municipal plants that treat sewage. Since 2001, the coverage of the ESR has been determined by the pollutant emissions of each company or facility and the total emissions of the district. 85% of the overall major pollutant emissions in a district are captured by the leading business or facilities. The major pollutants captured by the ESR are chemical oxygen demand, solid waste, sulfur dioxide, ammonia-nitrogen, and industrial soot. For the specific study, companies were matched in the two databases by “Legal Code”, in case of duplicates or missing codes, by “Company Name”, according to the method of Wang et al. (2018). Since the DEA -Malmquist index is measured for two time periods, only samples that lasted the study period were selected. In this work, a sample of 725 companies was selected for the period 2004-2012.

3.2.2. Water pollution index

In this paper, 725 national key monitoring intensive water polluted manufacturers in the YREB were selected from the report of China's Department of Environmental Protection from 2004 to 2012. In 2004, China began to intensify its efforts in water pollution control, and 2012 is the latest year for which data is available. The DEA/Malmquist index model states, the average number of employees and capital stock of enterprises was used as input. The total output value of industrial enterprises is considered as desired output, while CO_2, NH_3 and SO_2 are considered as undesired outputs.

(1) Capital stock. One of the input indicators is the capital stock. Since it is not possible to obtain capital stock data directly from the Statistical Yearbook, this paper uses the index of fixed investment for deflation. It takes into account the relative number of price trends and changes in the volume of investment in fixed assets over a given period. The formula for the fixed investment index can be expressed:

$$\mathrm{K} = \sum K_j \frac{W_j}{\sum W_j} \tag{8}$$

Where K is the total investment price index, K_j is the disaggregated price index and W_j is the weight.

(2) The number of employees. The number of employees is the second of the input indicators. Following Jiang et al. (2023), this paper adopts the average annual number of employees in the national key enterprises for monitoring water-intensive pollution enterprises in the YREB as the indicator of labour input.

(3) Industrial output. The desired output refers to the operator’s hope to obtain the maximum output with less input in the investment production process of the investment. In this paper, the YREB's major water-intensive polluting manufacturers' production value is selected as the desired output, and the two-digit ex-factory industrial price index is used to adjust the total industrial production value of the sub-industries to constant prices in 2004 to eliminate the influence of price fluctuation.

(4) Pollutant emissions. Literature introduces the generation and emission of pollutants in industrial sectors as an unwanted result to highlight the effects of pollution on productivity and the degree of greening of industrial production. In this paper, industrial emissions of CO_2, NH_3 and SO_2 in major national polluters are selected as indicators of undesirable output.

4. Results

4.1. Temporal changes in eco-efficiency

Using the DEA model, this study calculates eco-efficiency (*ML*) and its two decomposition *TC* and *TEC* for 725 nationally monitored polluting companies between 2004 and 2012, and presents the findings in Figure 1.

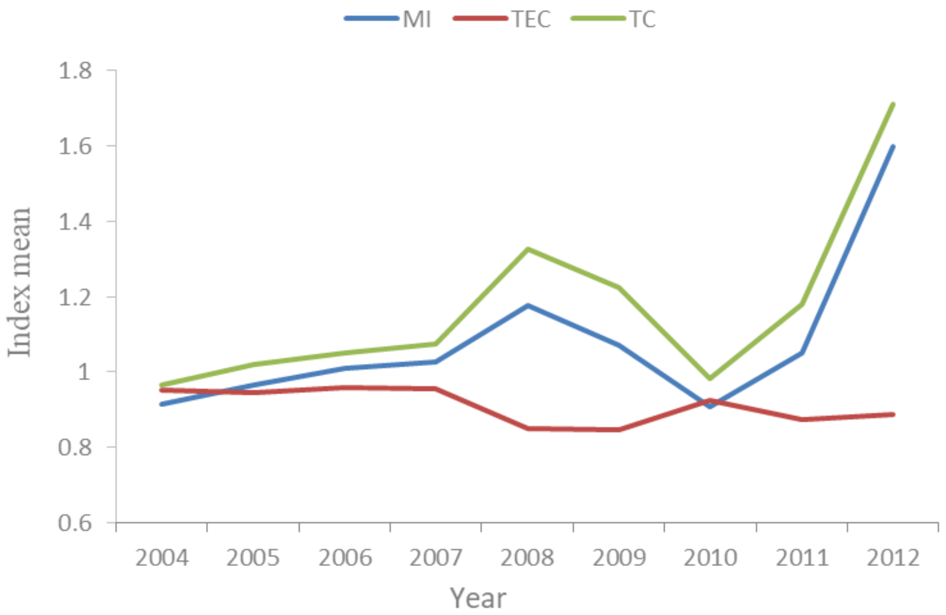

Figure 1. Ecological efficiency and decomposition items of key national monitoring water-intensive polluting manufacturers in the YREB (2004-2012).

4.1.1. Eco-efficiency (*ML*)

The Figure 1 shows that the eco-efficiency of the national key monitoring water intensive polluting manufacturers in the YREB generally showed an increasing trend from 2004 to 2012, and the eco-efficiency value was greater than 1 in all years except 2004, which was less than 1. This shows that the eco-efficiency of the YREB has improved with the continuous progress of the economy. Specifically, between 2004 and 2007, the eco-efficiency continuously increased from 0.982 to 1.076; however, between 2007 and 2010, the eco-efficiency fluctuated slightly, and the value of 1.037 in 2010 even showed a slight decrease compared to 2007. Considering the context at that time, it is possible that these companies were affected by the financial crisis in 2008 and that the output variable suffered. The output variable was affected by the financial crisis in 2008. Nonetheless, with national policies' backing, these enterprises in the YREB seized the opportunity and experienced a rebirth, and after 2010, eco-efficiency increased linearly to 1.152 in 2012.

4.1.2. Technical efficiency change (*TEC*)

The index of *TEC* of water-intensive polluting manufacturers under national supervision in the YREB is not optimistic. From 2004 to 2012, there has been a decline in *TEC*, which affects the improvement of eco-efficiency. In addition to the index of *TEC*, the level of industrial productivity has also declined, from 0.975 in 2004 to 0.942 in 2012, indicating that the reform of the system has reduced the efficiency of resource allocation.

4.1.3. Technological change (*TC*)

From Figure 1, the shape of the curve of the index of *TC* corresponds to eco-efficiency and goes through three phases: steady increase, slight decrease, and rapid increase. The industrial production of the YREB has been positively affected by independent innovation or technology introduction due to the continuous progress in technology level.

4.2. Spatial distribution of eco-efficiency

Using a total of 6,525 data from water-intensive polluting enterprises in the YREB, we selected the top 10% in terms of eco-efficiency, *TEC*, and *TC*, and the regions to which these enterprises belong. We studied the spatial distribution of eco-efficiency of water-intensive polluting manufacturers in the YREB by counting them.

4.2.1. Eco-efficiency (*ML*)

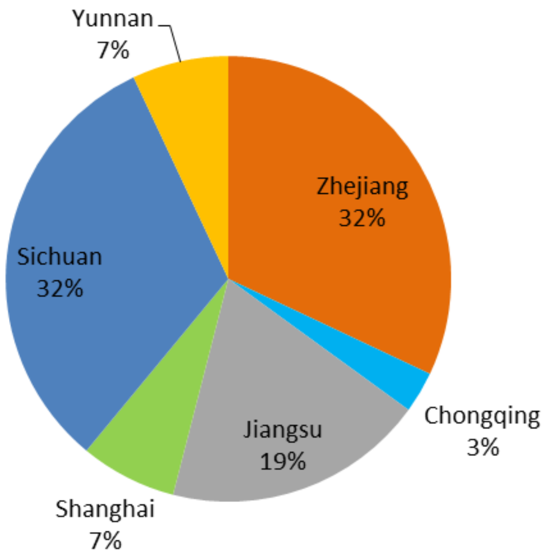

Figure 2. The province with the highest ecological efficiency enterprises between 2004 and 2012.

From Figure 2, 58% of eco-efficient enterprises are located in the low region, mainly in Zhejiang, Jiangsu and Shanghai, followed by Sichuan, Yunnan and Chongqing in the up region with 42%. It is worth noting that the middle region is not on the list.

The statistics show that Sichuan water intensive pollution enterprises are mainly concentrated in Neijiang, Leshan and Jinyang. In Neijiang, three water intensive pollution enterprises with high eco-efficiency are on the list: Sichuan Furen Meat Food Co Ltd, Sichuan Longchang Sihai Development Industrial Co Ltd and Jiejiang Huangtu Ceramics Co Ltd. These enterprises have had eco-efficiency scores in the top 10% for more than eight years. In Zhejiang Province, the companies on the list are mainly located in Hangzhou, Huzhou and Jiaxing. Among them, Hangzhou has the largest number of enterprises, namely Hangzhou Chun'an County Fenkou Silk Manufacturing Co Ltd, Hangzhou Jiali Cement Co Ltd, Puyangjiang Cement Co Ltd and Tonglu Jinzhong Paper Co Ltd. The companies in Jiangsu Province are more widely spread, selling in Nanjing, Xuzhou, Zhenjiang and Nantong.

4.2.2. Technical efficiency change (*TEC*)

From Figure 3, the top 10% of companies in terms of *TEC* are also located mainly in the low, with 74% of them. About half of these are located in Zhejiang; the next largest is in Jiangsu with 25%. 18% of enterprises are located in Chongqing, Sichuan, and Yunnan, the up regions. Similarly, the middle region is also not crowded with companies, with only one province, Hubei, accounting for 8%, and most of them located in Wuhan, Hubei.

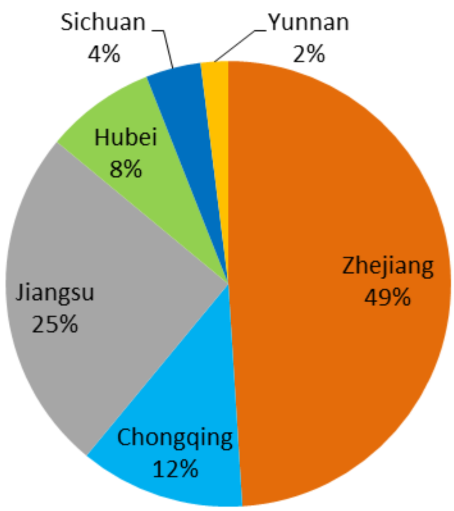

Figure 3. Provinces with enterprises in the top 10% for *TEC* between 2004 and 2012.

The majority of Zhejiang's companies are located in Wenzhou, Jiaxing, or Hangzhou. In Wenzhou, Zhejiang, the leather industry has a high level of *TEC*, with Zhejiang Huadu Leather Co Ltd and Zhejiang Wuxing Synthetic Leather Co Ltd ranking in the top 10% of all *TEC* scores between 2004 and 2012. As Wenzhou's leather industry has evolved over time, it tends to be mature, and its scale efficiency and pure *TEC* are high, hence its high *TEC*. Companies in Jiangsu are mainly located in the Suzhou and Wuxi areas. As a major textile and paper province, Jiangsu has high *TEC* in its paper and textile industries. Both Zhangjiagang Huyi Dyeing & Finishing Co Ltd in Suzhou and Rongcheng Paper Co Ltd in Wuxi were in the top 10% throughout the survey period. Chongqing in the up region also performs well, with Chongqing Feida Surface Treatment Centre, Chongqing Cummins Engine Co Ltd and Chongqing Xiaonanhai Cement Plant all in the top 10%. It can be noted that most of these companies are in the machinery manufacturing industry, as this is one of the city's strength. With a long history of development, experienced management, and a large market, Chongqing's machinery manufacturing industry is widely distributed in major industrial parks.

4.2.3. Technological change (*TC*)

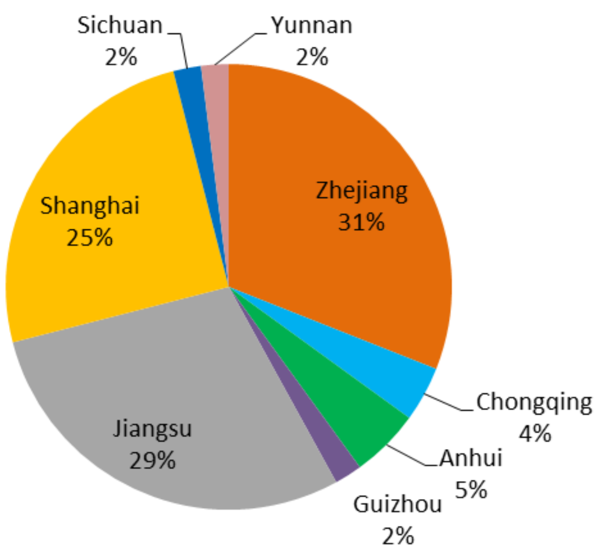

Figure 4. Provinces with enterprises ranked in the top 10% of the *TC* Index for five years or more (2004-2012).

According to Figure 4, the top 10% of companies in the *TC* Index are again mainly located in the low region, with a high proportion of 85%. Zhejiang, Jiangsu and Shanghai account for the largest share. The up regions of Chongqing, Sichuan and Yunnan account for 8% of the total. The middle region had the least number of companies, at 7%.

It is noteworthy that the distribution of these enterprises is more focused, mostly in cities with developed economies, mature technologies and experienced management. For instance, most of the Zhejiang companies here are from Taizhou, Jiaxing, Shaoxing and Jinhua. Jiangsu enterprises are also mostly located in the Nanjing, Jingjiang and Yangzhou areas. Throughout the survey period, Zhangjiagang Huyi Dyeing and Finishing Co., Ltd. also ranked in the top 10% of the *TC* index. As a result of these phenomena, there are significant differences in the *TC* index between cities and uneven development between them.

5. Spatial-temporal evolution across the Yangtze Economic Belt

5.1. Evolutionary characteristics over time

The results of the analysis show that the mean value for the eco-efficiency index for the entire sample period from 2004 to 2012 was 1.057 (see Figure 5). This indicates that eco-efficiency grew at an average pace of 5.7%.

Generally, the eco-efficiency of the water intensive polluting manufacturers under national key monitoring in the YREB is on an upward trend, and the eco-efficiency is greater than 1 in all years except for 2004, which is less than 1. This suggests that the ecological effectiveness of the YREB has improved with the continuous development of the economy.

As illustrated in Figure 5, the temporal changes in the eco-efficiency of water-intensive polluting manufacturers in the YREB can be broadly divided into three stages: 2004 to 2007, 2007 to 2010 and 2010 to 2012.

Between 2004 and 2007, the eco-efficiency of nationally monitored water intensive polluting manufacturers in the YREB showed an upward trend, with a three-year average of 1.033. The graph of the decomposition term shows that *TC* was an important driver of the rise in eco-efficiency at this time, which in turn was inextricably linked to the various foreign investment policies introduced following China's WTO admission in 2001. The increase in eco-efficiency indicates that China's throughout this time move towards the world has pushed up eco-efficiency. Meanwhile, many of China's environmental policies are in a stage of development and refinement, with many policies emerging from scratch: the decision on implementing the scientific outlook on development and strengthening environmental protection was promulgated by the State Council in December 2005. The Eleventh Five-Year Plan, which was implemented in 2006, set targets for the total amount of major pollutants to be controlled and connected the attainment of these targets to the performance of local government officials. The Eleventh Five-Year Plan for 2006 set aims for total control of major pollutants, and the scientific outlook on development and strengthening environmental protection decision was promulgated by the State Council in December.

Between 2007 and 2010, the eco-efficiency of water-intensive polluting manufacturers fluctuated slightly, with the value for 2010 even showing a slight decrease compared to 2007, at 1.037, a decrease of 3.9%. Combined with the context of the time, it can be inferred that these enterprises at this time were affected by the financial crisis in 2008, which reduced foreign investment and affected *TC* and *TEC*. At the same time, the output variable of eco-efficiency was hit by the disruption of the enterprises' overseas trade during this period.

Between 2010 and 2012, there was a great increase in the eco-efficiency of water-intensive polluting manufacturers. By 2012, eco-efficiency had risen to 1.152. The source of the increase was still mainly technological development. The increase in *TC* is linked to the 'quadrillion' stimulus package introduced in China after the economic crisis, which brought about technological spillover effects. At the same time, in terms of environmental policy, the 17th Party Congress proposed speeding up the shift in the mode of economic growth, and for the first time proposed the strategic task of building an ecological civilization. The construction of an ecological civilization was once again integrated by the 18th Party Congress into the general framework of the Chinese-style "five-in-one" socialism. These policies have demonstrated the Party's and the government's commitment to addressing environmental pollution.

5.2. Spatial distribution

This paper classifies Shanghai, Zhejiang and Jiangsu as the lower region, Anhui, Jiangxi, Hubei and Hunan as the middle region, and Chongqing, Sichuan, Yunnan and Guizhou as the upper region to analyze the interregional differences in the eco-efficiency of water intensive polluting manufacturers in the YREB. To ensure that show the spatial traits of evolution more intuitively, this study use STATA software to create a geographical eco-efficiency distribution of water-intensive polluting manufacturer in the YREB in 2004 , 2006, 2009 , 2012, and the outcomes are displayed in Figure 5.:

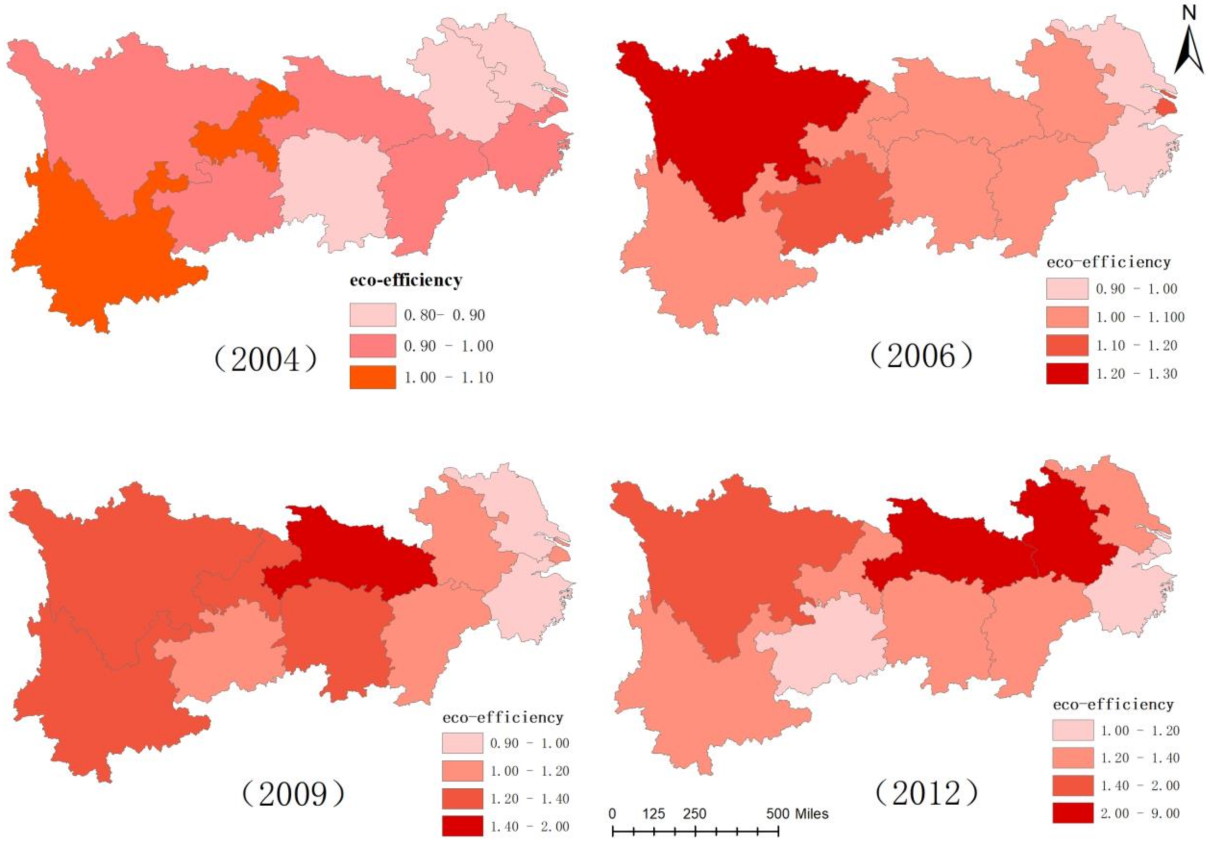

Figure 5. Spatial distribution of eco-efficiency of national key monitoring water-intensive polluting manufacturers in the YREB in 2004, 2006, 2009, 2012.

Data source: Data of national key monitoring water intensive polluting manufacturer

As showed in Figure 5, the overall eco-efficiency of water-intensive polluting manufacturers in the YREB is low at this time.

The eco-efficiency of the key national monitoring polluters in the YREB in 2004 was divided into three ranges, 0.8-0.9, 0.9-1.0, and 1.0-1.1, with the darker color indicating higher eco-efficiency. It is evident that the highest eco-efficiency is found in Yunnan, and Chongqing, followed by Guizhou, Shanghai, Jiangxi, Sichuan, Zhejiang, Hubei, and the lowest in Anhui, Jiangsu, Hunan. Thus, it can be concluded that in 2004, the distribution pattern of eco-efficiency from high to low is: up region> middle region> low region. Similarly, Zhou et al. (2020) examined the distribution of eco-efficiency among cities in China in 2004 and found that the most eco-efficient regions were in the middle and up regions. The reason for this situation is that China was still in its early stages of economic development in 2004 and 2006. After the reform and opening up, the state put forward the slogan of "the rich first lead the rich later and run for prosperity together" and implemented the strategy of giving priority to the development of the low region, investing an enormous of capital and policy support in the low, but, due to the lack of technological experience during that period, the development emphasized speed over quality, and was a rough and loose development, developing mostly high pollution, high energy, and high water consumption enterprises. "Three high" enterprises, this development at the cost of the environment, ecological efficiency are low. At this time, the financial progress of the middle and up regions is backward, and the industrial structure is mainly light industry, which is less polluting and therefore more eco-efficient in comparison.

As shown in Figure 5, it can be seen that the eco-efficiency of polluters in each region in 2012 has increased significantly compared to 2004. The eco-efficiency is divided into five intervals, 1.0 to 1.2, 1.2 to 1.4, 1.4 to 2.0, and 2.0 to 9.0. The darker the color on the graph means the higher the eco-efficiency. Evidently, the highest eco-efficiency is found in Hubei and Anhui, followed by Sichuan, Jiangxi, then Chongqing, Yunnan, Guizhou, Jiangsu, Hunan and finally Zhejiang, Shanghai.

Thus, it can be said that in 2012, the distribution pattern of eco-efficiency from high to low is: Middle> Up> Low. Although the low region has seen a significant increase in eco-efficiency, it is still lower compared to the middle and up regions. This result differs from numerous inter-provincial eco-efficiency measures of the YREB in the literature. In previous literature, literature has often concluded that the low region is more eco-efficient. For example, Humaira et al. (2020), Tu et al. (2019), Hao et al. (2022) all concluded that the eco-efficiency of the YREB in 2012 showed a decreasing feature from low to up. While this inconsistent result is partly due to the different indicators and analytical tools chosen, this paper suggests that there are two main reasons for this discrepancy: firstly, it may be due to the differences in the research objects of this paper and other articles. This paper focuses on water intensive polluting manufacturers that is the focus of national monitoring, and because the low part of the YREB has a natural geographical advantage, many of these enterprises, which are still highly polluting heavy industries even among water intensive polluting manufacturers, such as steel, chemical and cement industries, are clustered in the low part of the region for transport convenience, making it difficult to increase the region's eco-efficiency significantly. Secondly, this is also related to the highly uneven inter-city development of the low region. As mentioned earlier, although some developed cities in the low region are more eco-efficient due to their technological and financial advantages, however, due to uncoordinated inter-regional development, many underdeveloped cities in the low region are also very eco-efficient and appear to be less productive than the average productivity of the middle and up regions, pulling down the average eco-efficiency of the low region. At the same time, the significant improvement in eco-efficiency in the middle and up regions is partly due to the implementation of the tactic of the rise of the development of the up regions and middle China, but also because these regions are mostly distributed by water intensive polluting manufacturers with lighter pollution levels.

It is worth noting that Anhui province, which had the lowest eco-efficiency in 2004, became the most efficient in 2012. The reason for this should be that it has leveraged the advanced environmental technology and management experience of the neighbouring low regions, which have contributed to the province's level of green *TC* and improved green technological efficiency change (*TEC*).

6. Conclusions

This study quantitatively evaluates the ecological efficiency of pivotal water-intensive polluting enterprises within the YREB from 2004 to 2012, utilizing the DEA model. Furthermore, it dissects the contributions of technological advancements (TC) and shifts in technical efficiency (TEC) to the trajectory of China's green industrial development, employing the decomposition facet of the Malmquist index in both temporal and spatial dimensions.

Our analysis of three critical indices, namely ecological efficiency, shifts in technical efficiency (TEC), and technological advancements (TC), for principal national monitoring pollutants in the YREB over the 2004-2012 span yields several notable findings:

Temporal Evolution: The eco-efficiency of these key monitored, water-intensive polluting entities exhibited a generally ascending trend from 2004 to 2012, signifying a transition towards a sustainable developmental paradigm that's both resource-conservative and environmentally amicable. This trajectory predominantly stems from technological advancements (TC) anchored in national strategic innovation directives, accentuating indigenous innovation capabilities. However, stagnant technical efficiency (TEC) acts as a significant impediment to heightened eco-efficiency. Given that EC is influenced by managerial competencies, institutional frameworks, technological adoption, and production scale, the observed stagnation likely arises from managerial deficiencies and systemic inefficiencies, culminating in market resource misallocation. Three distinct phases demarcate the temporal eco-efficiency shifts: 2004-2007, 2007-2010, and 2010-2012, each intimately entwined with national environmental policy proclamations and global economic climates.

Spatial Development: Examining the eco-efficiency of water-intensive polluting enterprises across lower, middle, and upper echelons of the YREB, it's evident that both the TEC and TC indices for enterprises in the lower belt surpass their counterparts in the middle and upper regions during 2004-2012. This indicates a superior policy framework, technological milieu, and investment ambiance in the lower belt. Contrary to conventional wisdom, our findings spotlight the upper belt as outperforming the middle belt, attesting to significant state-led developmental initiatives targeted at the former. This comprises fiscal injections, educational bolstering, transfer payments, and an enhanced investment climate. Meanwhile, the middle belt exhibited a lackluster performance, potentially reflecting governmental neglect. On the city-level granularity, even within the advanced lower belt, eco-efficient enterprises are predominantly clustered in provinces like Jiangsu and Zhejiang, specifically within cities such as Nanjing, Suzhou, Hangzhou, Shaoxing, and Wenzhou. In the upper belt, a staggering 90% of entities are anchored in Chengdu and Chongqing, highlighting pronounced developmental disparities across regions.

Spatial Distribution Dynamics: The 2004 and 2012 spatial distribution snapshots indicate superior eco-efficiency for enterprises in the middle and upper belts compared to the lower belt. This likely stems from the preponderance of high-pollution, heavy industries in the lower belt, attracted by logistical advantages. Furthermore, numerous water-intensive polluting entities in the nascent cities of the lower belt register eco-efficiencies significantly below the mean scores of the middle and upper belts.

In essence, this comprehensive exploration underscores the intricate interplay of technological progress, institutional reforms, and spatial dynamics in shaping the eco-efficiency trajectory of water-intensive polluting entities within the YREB.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Author contributions

MC: conceived the research idea and wrote the manuscript. ZD: conducted the analysis. All authors contributed to the article and approved the submitted version.

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