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A Study on the Efficiency of Regional Water Resource Utilization in China: Based on the Three-Stage Data Envelopment Analysis (DEA)-Malmquist Method

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Abstract: To objectively evaluate the efficiency of water resource utilization in 31 provinces (municipalities and autonomous regions) of China from 2015 to 2024 and effectively eliminate the effects of environmental factors and random disturbances, this study employs a three-stage data envelopment analysis (DEA) model and the Malmquist index method to construct an evaluation system for water resource utilization efficiency from an input-output perspective. The results show that: (1) environmental factors and random disturbances exert significant effects on the measured efficiency of water resource utilization, and the traditional DEA model overestimates efficiency in the eastern region while underestimating it in the central and western regions; (2) from 2015 to 2024, the overall efficiency of water resource utilization in China exhibited a fluctuating upward trend, with marked regional disparities, the highest efficiency in the eastern region, and relatively lower efficiency in the central and western regions; (3) technological progress is the core driver of efficiency improvement, whereas managerial inefficiency is the key factor constraining efficiency gains in some provinces; and (4) per capita water resources and industrial structure exert heterogeneous effects on water resource utilization efficiency. Accordingly, it is essential to further upgrade the structure of the industry, strengthen interregional diffusion and coordinated application of technologies, and implement differentiated water resource management policies to promote efficient water use and sustainable development.

Keywords: Water resource utilization efficiency, three-stage DEA, Malmquist index, environmental factors, regional disparities.

1. Introduction

Water resources are a fundamental natural resource and a strategic economic resource underpinning sustainable socioeconomic development, and they are also a core element for maintaining ecosystem balance [1]. China's long-term average total water resources amount to approximately 2.8 trillion m³, ranking sixth in the world. However, owing to its large population base, per capita water resources in China were only about 2208.9 m³ in 2024 [2], merely one-quarter of the world average. Moreover, the spatial distribution is highly uneven: some regions are relatively water-abundant, whereas others, such as North China, face extremely limited surface water resources [3]. Temporally, precipitation is also uneven, with a substantially higher share concentrated in the flood season. Regarding water-use efficiency, water consumption per CNY 10,000 of GDP in China was about 47 m³ in 2024; although this represents a decline relative to 2015, it still remains above the level of advanced countries. Water pollution has not yet been fundamentally resolved. In 2024, sections with Grade IV or worse surface-water quality still accounted for 9.6% nationwide [4], and agricultural non-point-source pollution and industrial point-source pollution continued to threaten water quality. Meanwhile, China's resident urbanization rate increased from 49.70% in 2010 to 63.9% in 2020 [2]. At present, China is at a critical stage in the transition toward high-quality water conservancy development, which places higher requirements on national water security capacity building.

Traditional data envelopment analysis (DEA) models, which do not require a prespecified production function, have been widely applied to efficiency evaluation of decision-making units. However, they do not account for environmental factors and random disturbances, which may lead to biased efficiency estimates [5]. By introducing stochastic frontier analysis (SFA) to separate environmental effects, managerial inefficiency, and random noise, the three-stage DEA model can more objectively reflect the true efficiency of decision-making units. Accordingly, utilizing provincial panel data spanning 2015–2024, this paper applies the three-stage DEA model to isolate environmental variables and statistical noise, while incorporating the Malmquist index to analyze dynamic efficiency evolution, thereby offering robust empirical evidence for improving water resource utilization efficiency.

At present, scholars at home and abroad have conducted extensive theoretical and practical research on the evaluation of water resource utilization efficiency. In international studies, Fare et al. (1994) were the first to apply the DEA model to resource-efficiency evaluation, laying the theoretical foundation for this approach [6]. Long L et al. estimated urban eco-efficiency using a super-efficiency SBM-DEA model that incorporates undesirable outputs [7]. Some studies have employed the DEA-SBM approach to evaluate economic efficiency and the DEA undesirable-output approach to assess environmental efficiency [8]. In domestic research, Zhang Zhaofang et al. combined the model of super-efficiency DEA, the method of Malmquist index, and a unique model of Tobit to investigate water resource utilization efficiency in 18 provinces and municipalities along the Belt and Road from 2011 to 2015, and found that overall water-use efficiency increased, with the southeast outperforming the northwest, the northwest outperforming the northeast, and the northeast outperforming the southwest;

total factor productivity growth was mainly driven by technological progress, per capita GDP had a positive effect, and the agricultural water-use structure had a negative effect [9]. At the interprovincial level, Jiang Dejuan et al. used DEA and the Malmquist index to analyze water resource utilization efficiency in 16 prefecture-level cities in Shandong Province from 2011 to 2020 and similarly concluded that total factor productivity growth was mainly attributable to technological progress [10]. At the basin scale, Zhang Yan et al. applied a super-efficiency slack-based measure (SBM) model to evaluate water resource efficiency in the Yellow River Basin and found that agricultural water-use efficiency there was generally on an upward trajectory, with technological progress as the key factor improving agricultural water-use efficiency [11]. Also focusing on the Yellow River region, Cheng Xiejun et al. provided a deeper analysis of agricultural production efficiency. Their results showed that aggregate productivity growth about the Yellow River Basin was mainly attributable to innovation-driven progress rather than efficiency improvement, highlighting the importance of continuous innovation and technological application for maintaining agricultural productivity [12]. Wang Chao et al. used DEA and the method of Malmquist index to study the mainstream area of the Hanjiang River and demonstrated, through efficiency comparisons across the study area, the importance of technological progress for total factor productivity [13].

In summary, existing studies have generated rich findings, mainly focusing on super-efficiency DEA models and covering regional comparisons of utilization efficiency and the major determinants of total factor productivity growth. Nevertheless, there is still room for improvement. First, most studies focus on short-term datasets (5-8 years), lacking dynamic tracking of long time series of 10 years or more. Second, some studies fail to fully account for the heterogeneous effects of environmental factors, leading to insufficiently precise efficiency evaluation. Accordingly, this study uses provincial panel data for 2015-2024, applies the three-stage DEA model to eliminate the factors of environmental and random disturbances, and combines it with the Malmquist index to analyze dynamic efficiency changes, in order to provide more comprehensive empirical support for improving water resource utilization efficiency.

2. Research Methods and Data Sources

2.1. Research Framework

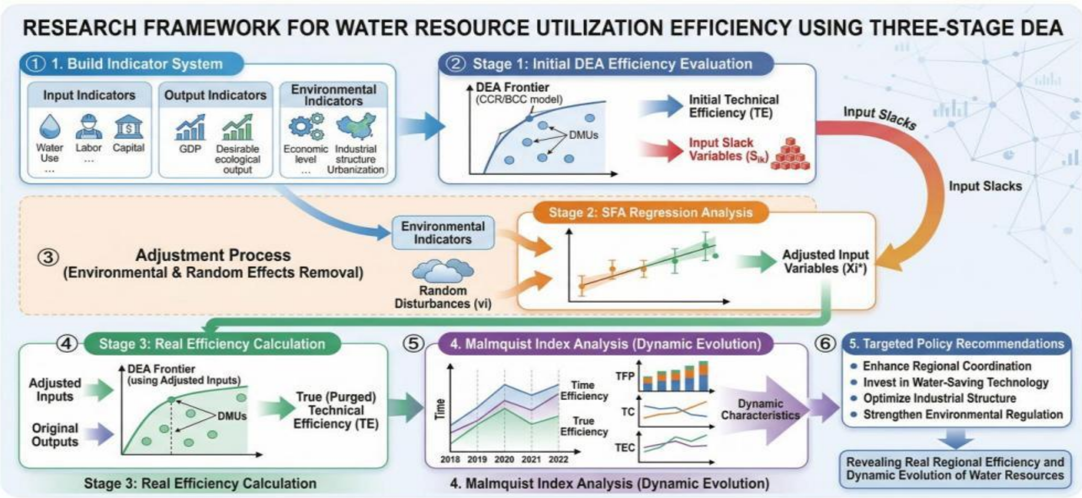

Figure 1. Research framework diagram

The analytical framework of this study is as follows and this framework ensures effective separation of environmental effects and random errors, thereby underscoring variations in the actual technical efficiency of regional water resource utilization, as illustrated in Figure 1.

2.2. Research Methods

2.2.1. Panel Three-Stage DEA

The three-stage DEA method was proposed by Fried et al. It posits that efficiency losses are jointly caused by random disturbances, managerial inefficiency, and the external environment; therefore, if managerial efficiency is to be evaluated, the effects of external environmental factors and random disturbances must be removed from the observed efficiency loss [14]. Compared with the traditional DEA model, this model takes time into account, and related studies usually concern long-term processes. There is a time lag between inputs and outputs. The three-stage DEA model can therefore provide a more accurate evaluation of input-output efficiency and better handle temporal relationships.

The specific steps of the panel three stages of DEA are as follows. In the first stage, a traditional DEA model can be used. Under the assumption of variable returns to scale (VRS), an input-oriented BCC model is constructed. Suppose there are n decision-making units (DMUs), and each DMU contains m input variables and s output variables. Let the input matrix be X = (x_{rj})(m×n), and the output matrix be Y = (y_{rj})_(s×n). Then the efficiency value of the jth DMU θ_j is obtained by solving the following linear program: $\min \theta_j - \varepsilon(\sum_{i=1}^{m} s_i^- + \sum_{r=1}^{s} s_r^+)$

$$\text{s.t.} \begin{cases} \sum_{j=1}^{n} \lambda_j x_{ij} + s_i^- = \theta_j x_{ij}^0 \\ \sum_{j=1}^{n} \lambda_j y_{rj} - s_r^+ = y_{rj}^0 \\ \sum_{j=1}^{n} \lambda_j = 1 \\ \lambda_j \geq 0, s_i^- \geq 0, s_r^+ \geq 0 \end{cases} \tag{1}$$

Where $\theta_j \in [0, 1]$ denotes the comprehensive technical efficiency score, λ_j is the weight coefficient, s_i^- and s_r^+ are the input and output slack variables, respectively, and ε is a non-Archimedean infinitesimal.

In the second stage, namely the SFA regression model, a panel stochastic frontier model is used to analyze slack values, distinguish the impacts of exogenous environmental factors, random disturbances, and managerial inefficiency on the slacks, and obtain adjusted values under the same external environment and random disturbance. Taking the input slack variables obtained in the first stage as the dependent variables and the environmental variables as the explanatory variables, an SFA regression model is constructed to separate environmental factors (Z_j), managerial inefficiency (u_{ij}), and random disturbance (v_{ij}). The specific formula is as follows:

$$s_{ij}=f\left(Z_j;\beta_i\right)+v_{ij}+u_{ij} \quad (2)$$

In this equation, s_{ij} denotes the slack value associated with the ith input for the jth decision-making unit (DMU). $f(Z_j;\beta_i)$ is the effect function of environmental factors (specified in semi-logarithmic form), β_i signifies the unknown coefficient that requires calibration, v_{ij} stands for the stochastic disturbance term with $v_{ij}\sim N(0,\sigma_i^2)$; u_{ij} is the managerial inefficiency term, which is assumed to follow a half-normal distribution $u_{ij}\sim N+(\mu i,\sigma_i^2)$. After the parameters are estimated by maximum likelihood, the conditional expectation of the managerial inefficiency term is calculated following the method proposed by Jondrow et al., E[uij|vij+uij], and the original input variables are adjusted as follows:

$$x_{ij}^*=x_{ij}-\left[f\left(Z_j;\hat{\beta}_i\right)-f\left(Z_{min};\hat{\beta}_i\right)\right]-\left[E\left(u_{ij}|v_{ij}+u_{ij}\right)-E\left(u_{imin}|v_{imin}+u_{imin}\right)\right] \quad (3)$$

Where x_{ij}^* is the adjusted input variable, and Z_{min} is the optimal level of the environmental variable, ensuring that all DMUs are under the same environmental and managerial conditions.

In the third stage, an adjusted DEA model is employed. Under a unified frontier across different years, the output values and adjusted input values are re-entered for DMU evaluation. Specifically, the variables x_{ij}^* is the adjusted input and the original output variables Y are substituted into the BCC model to recalculate efficiency. This value is the true water resource utilization efficiency after removing environmental factors and random disturbances.

2.2.2. Malmquist Index Model

The Malmquist index model was proposed by Malmquist and is a dynamic efficiency analysis method based on the DEA framework; it is also commonly referred to as the total factor productivity (TFP) index model. This model can be used to analyze changes in resource utilization efficiency and their driving factors. The specific formulation of the Malmquist index is as follows:

$$M_{t,t+1}\left(x_t,y_t,x_{t+1},y_{t+1}\right)=\sqrt{\frac{D_{t+1}\left(x_{t+1},y_{t+1}\right)}{D_t\left(x_t,y_t\right)}\times\frac{D_t\left(x_{t+1},y_{t+1}\right)}{D_{t+1}\left(x_t,y_t\right)}}=EC\times TC \quad (4)$$

To analyze dynamic efficiency changes, the index of Malmquist that is decomposed into efficiency change (EC) and technological change (TC). Here, $D_t\left(x_t,y_t\right)$ and $D_{t+1}\left(x_{t+1},y_{t+1}\right)$ are the distance functions for period t and period t+1, respectively; EC>1 indicates an improvement in technical efficiency, TC>1 indicates technological progress, and M>1 indicates growth in total factor productivity.

The Malmquist index model can decompose total factor productivity (TFP) into the advanced of technology efficiency TECHCH, pure technical efficiency change PECH, and scale efficiency change SECH.

$$TFP_t^{t+1}=TECHCH_t^{t+1}\times PECH_t^{t+1}\times SECH_t^{t+1} \quad (5)$$

Following the practices of scholars such as Sun Caizhi and Lu Xi, this study adopts the three-stage DEA-Malmquist index model to measure regional water resource utilization efficiency in China and to investigate its dynamic changes and driving factors. The decomposed technological change efficiency, pure technical efficiency change, and scale efficiency correspond respectively to technological progress, management level, and scale economy factors affecting regional water resource utilization efficiency in China.

2.3. Data Sources and Indicator Selection

2.3.1. Data Sources

The dataset covers 31 provinces in China from 2015 to 2024. Owing to data availability, Hong Kong, Macao, and Taiwan are not included in the sample. The data are mainly drawn from China Statistical Yearbook (2016-2025), China Water Resources Bulletin (2016-2025), and provincial statistical yearbooks. Missing observations were supplemented using linear interpolation.

2.3.2. Indicator Selection

Referring to the existing literature and considering the broad scope of regional water resources in China, as well as the need to ensure the reliability of the findings and data availability, this study selects the following indicators as output, input, and environmental variables [9]-[10], as shown in Table 1.

Table 1. Indicator system for evaluating regional water resource utilization efficiency in China using the three-stage DEA

Indicator	Indicator Name	Indicator Description	Unit
Input Indicator	Annual Industrial Water Consumption	Industrial water consumption	10^8 m³
	Annual Agricultural Water Consumption	Agricultural water consumption	10^8 m³
	Annual Domestic Water Consumption	Domestic water consumption	10^8 m³
	Artificial Ecological Water Replenishment	Ecological and environmental water consumption	10^8 m³
	Water-Using Population	Labor input	10,000 persons
	NH_3-N Emissions	Waste output	10,000 tons
Output Indicator	Regional Gross Domestic Product	Economic output	CNY 100 million

Table 2. Definitions and descriptions of environmental variables

Variable Category	Variable Name	Variable Definition	Unit
Environmental Variable	Per Capita Water Resources	Quantitative measure of water resource endowment	m³/ person
	Value Added of the Primary Industry	Measure of agricultural structure	CNY 100 million
	Value Added of the Secondary Industry	Measure of industrial structure	CNY 100 million

3. Empirical Results and Analysis

3.1. First-Stage Traditional DEA Efficiency Analysis

Table 3 reports the mean water resource utilization efficiency of 31 provinces in China from 2015 to 2024. The mean comprehensive technical efficiency (CRSTE) calculated by the traditional DEA model is 0.824. In terms of regional distribution, eastern provinces such as Beijing, Shanghai, Jiangsu, Zhejiang, and Fujian exhibit the highest efficiency (all lying on the efficiency frontier with a value of 1), whereas the northeastern and western regions perform less well. Provinces with efficiency values above 0.9 are concentrated mainly in the east (e.g., Beijing, Shanghai, Jiangsu, and Zhejiang), where economic development is more advanced, technologies are more sophisticated, and water resource allocation is more rational. Provinces with efficiency values below 0.6 are mainly located in the west and northeast (e.g., Jilin, Heilongjiang, and Gansu), where water resource utilization efficiency is constrained by natural and economic conditions.

Table 3. Mean regional water resource utilization efficiency in China, 2015-2024 (Stage I)

Region	10-Year Mean CRSTE	Rank	Region	10-Year Mean CRSTE	Rank
Beijing	1.000	1	Henan	0.800	17
Shanghai	1.000	1	Hubei	0.799	18
Jiangsu	1.000	1	Hunan	0.798	19
Zhejiang	1.000	1	Hebei	0.796	20
Fujian	1.000	1	Jiangxi	0.792	21
Shandong	1.000	1	Shanxi	0.755	22
Chongqing	0.980	7	Anhui	0.744	23
Tianjin	0.961	8	Ningxia	0.666	24
Shaanxi	0.956	9	Xinjiang	0.659	25
Guizhou	0.948	10	Guangxi	0.647	26
Hainan	0.941	11	Liaoning	0.626	27
Guangdong	0.919	12	Qinghai	0.620	28
Yunnan	0.894	13	Gansu	0.596	29
Inner Mongolia	0.890	14	Heilongjiang	0.584	30
Sichuan	0.852	15	Jilin	0.496	31
Tibet	0.836	16	National	0.824	-

Note: Hong Kong, Macao, and Taiwan are excluded.

Table 4. Mean water resource utilization efficiency in eastern, central, and western China, 2015-2024 (Stage I)

Region	Mean	Group Maximum	Group Minimum
Eastern Region	0.931	1.000	0.626
Central Region	0.721	0.800	0.496
Western Region	0.795	0.980	0.596

Note: In this study, the eastern, central, and western regions are delineated based on provincial composition. Specifically, the east consists of Beijing, Tianjin, Hebei, Liaoning, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong, and Hainan; the central region consists of Shanxi, Anhui, Jiangxi, Henan, Heilongjiang, Jilin, Hubei, and Hunan; and the west consists of Inner Mongolia, Guangxi, Chongqing, Sichuan, Guizhou, Yunnan, Tibet, Shaanxi, Gansu, Qinghai, Ningxia, and Xinjiang. It should be noted that Hong Kong, Macao, and Taiwan are excluded from the analysis.

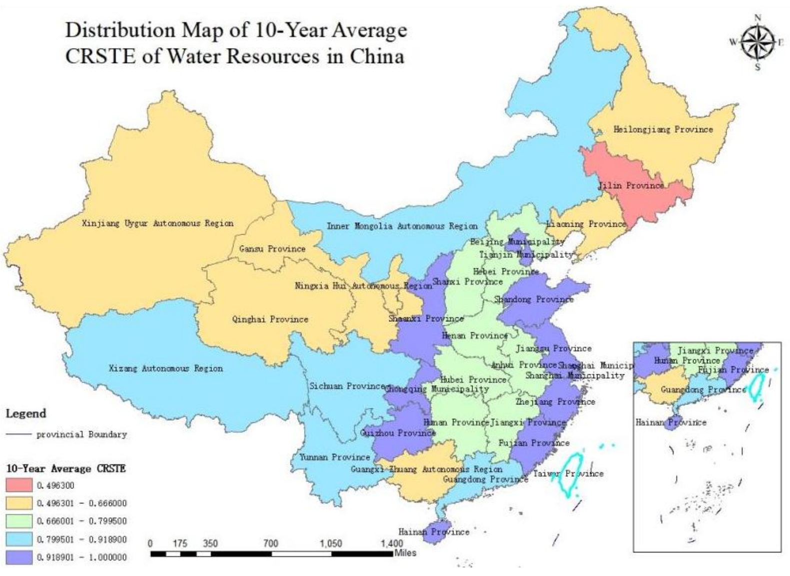

Figure 2. Spatial distribution of the 10-year mean CRETE of water resources in China

According to the classification and adjustment in China Environmental Statistical Yearbook, this study divides

China's provincial-level administrative units into three major regions-eastern, central, and western-for comprehensive analysis (Table 4). The eastern region where economic development is relatively advanced and agricultural development is often constrained by industrial and other economic development. The central region includes provinces such as Henan, Jiangxi, and Anhui; precipitation, temperature, and sunshine conditions are relatively suitable for agricultural production, making this region one of China's main grain-producing areas. The western region includes provinces such as Qinghai, Shaanxi, and Inner Mongolia; it features highly diverse topography, including mountains, hills, and deserts, and is generally less suitable for agricultural production. As shown in Table 4, from 2015 to 2024 the mean efficiency of water resource utilization across the three major regions of eastern, central, and western China displayed significant regional heterogeneity. The eastern region ranked first with a mean efficiency of 0.931 and a group maximum of 1.000, indicating the presence of fully efficient units. The western region ranked second with a mean of 0.795 and a group maximum of 0.980, close to the efficient frontier. By contrast, the central region had the lowest mean value, only 0.721, and the group minimum of 0.496, making it the region with the most pronounced internal differentiation in efficiency. In terms of within-group extremes, the group minimum was 0.626 in the east, 0.596 in the west, and 0.496 in the center, indicating that the internal regional gap in water resource utilization efficiency is far greater in central China than in the eastern and western regions.

3.2. Second-Stage SFA Regression Analysis

In this stage, we set the six input redundancy variables as the outcome variables, and the three exogenous environmental indicators as the predictor variables. SFA regression estimation was then implemented using the Frontier 4.1 software package, and the detailed estimation results are displayed in Table 5. As shown, all γ values are close to 1 (0.922–1.000) and statistically significant at the 5% level. This finding verifies that the majority of the variation in input slack variables stems from managerial inefficiency, which in turn validates the applicability of the SFA model in this study.

Table 5. Core results of the second-stage SFA regression (2024 as an example)

Input Slack Variable	Per Capita Water Resources (β_1)	Value Added of the Primary Industry (β_2)	Value Added of the Secondary Industry (β_3)	γ Value	R^2
Industrial Water Consumption	0.003	0.001	-0.000	1.000	0.997
Agricultural Water Consumption	0.201	0.027	-0.003	0.922	0.985
Domestic Water Consumption	0.001	0.003	-0.000	0.840	0.912
Ecological Water Replenishment	0.008	0.001	-0.000	1.000	0.995
Water-Using Population	0.161	0.047	-0.008	1.000	0.992
NH_3-N Emissions	0.001	0.000	-0.000	1.000	0.989

The regression results indicate that: (1) per capita water resources (β_1) are significantly positively correlated with the slacks of industrial water use, agricultural water use, and ecological replenishment, suggesting the existence of a "resource curse" phenomenon in regions with richer water endowment, where water use tends to be more extensive; (2) value added of the primary industry (β_2) is significantly positively correlated with most input slacks, indicating that a higher agricultural share is associated with more serious redundancy in water consumption and pollution emissions that is congruent with the reality of relatively low agricultural water-use efficiency; and (3) value added of the secondary industry (β_3) is significantly negatively correlated with the slacks of industrial and agricultural water consumption, indicating that improvements in industrial modernization help reduce water resource redundancy and that technological progress plays a facilitating role in efficiency enhancement.

3.3. Third-Stage Adjusted DEA Efficiency Analysis

After removing environmental factors and random disturbances, the third-stage efficiency values can better reflect the true efficiency of water resource utilization (Table 6). The national mean comprehensive technical efficiency declines from 0.824 in the first stage to 0.736, indicating that the traditional DEA model overestimates water resource utilization efficiency. The changes in the high efficiency of eastern provinces are relatively small, mainly owing to their favorable environmental and economic conditions, whereas the effect of true managerial capability is relatively smaller.

At the provincial level, the third-stage efficiency values of Beijing, Shanghai, and Jiangsu remain above 0.9, indicating that these provinces not only enjoy favorable environmental and economic conditions but also possess more efficient water resource management. After adjustment, the efficiency of Tibet and Ningxia increases by 8%, suggesting that natural environmental constraints are the main reason for their relatively low efficiency. By contrast, the efficiency of major agricultural provinces such as Hebei decreases by 8%-10% after adjustment, indicating prominent managerial inefficiency in their water resource utilization.

Table 6. Mean regional water resource utilization efficiency in China, 2015-2024 (Stage III)

Region	10-Year Mean CRSTE	Rank	Region	10-Year Mean CRSTE	Rank
Beijing	1.000	1	Ningxia	0.749	17
Guizhou	1.000	1	Guangdong	0.748	18
Sichuan	1.000	1	Inner Mongolia	0.719	19
Hunan	1.000	1	Shanxi	0.706	20
Hainan	0.999	5	Hebei	0.673	21
Shanghai	0.992	6	Yunnan	0.607	22
Shaanxi	0.917	7	Xinjiang	0.604	23
Tibet	0.916	8	Shandong	0.589	24
Jiangsu	0.907	9	Tianjin	0.539	25
Anhui	0.898	10	Jiangxi	0.502	26
Liaoning	0.880	11	Qinghai	0.491	27
Fujian	0.860	12	Chongqing	0.448	28
Hubei	0.841	13	Heilongjiang	0.353	29
Zhejiang	0.791	14	Gansu	0.284	30
Jilin	0.779	15	Guangxi	0.259	31
Henan	0.770	16	National	0.736	-

Note: Hong Kong, Macao, and Taiwan are excluded.

3.4. Dynamic Analysis of the Malmquist Index

To further examine the dynamic evolution of water resource utilization efficiency in China from 2015 to 2024, the Malmquist index is used to decompose Total Factor Productivity (TFP) into Efficiency Change (EC) and Technological Change (TC), as shown in Table 7. The results indicate that the mean TFP was 1.07 during 2015-2024, implying an average annual growth rate of 7% and an overall improvement in dynamic water-use efficiency. The mean TC index was 1.065, exceeding 1 and substantially surpassing the mean EC index, indicating that technological progress was the primary driver of TFP growth. This suggests that China achieved notable progress in the development, diffusion, and application of water-saving technologies, which strongly supported efficiency improvement. In contrast, the mean EC was 1.005, only slightly above 1, indicating a limited improvement in water resource management. Fluctuations in managerial efficiency partly constrained the stable growth of TFP, which is consistent with the third-stage DEA results.

The direction of efficiency change can be identified by comparing the EC index with 1: values above 1 indicate growth, values below 1 indicate decline, and a value equal to 1 indicates no change. From a yearly perspective, the TFP indices for 2015-2016, 2016-2017, 2020-2021, and 2022-2023 were 1.391, 1.166, 1.304, and 1.358, respectively, indicating significant efficiency growth. The strongest growth occurred in 2015-2016 and 2022-2023, likely driven by the joint contribution of technological progress and technical efficiency, both of which exceeded 1. By contrast, the TFP index was below 1 in 2017-2018, 2019-2020, 2021-2022, and 2023-2024, indicating efficiency decline, with the largest decrease in 2023-2024. This downturn was mainly caused by regression in the technological change index, while the decline in technical efficiency further intensified the reduction in efficiency.

Table 7. Malmquist index decomposition, 2015-2024

Period	TFP Index	Efficiency Change (EC)	Technological Change (TC)
2015-2016	1.391	1.017	1.369
2016-2017	1.166	1.057	1.103
2017-2018	0.931	1.000	0.931
2018-2019	1.094	0.969	1.129
2019-2020	0.906	0.999	0.907
2020-2021	1.304	1.091	1.195
2021-2022	0.977	0.950	1.028
2022-2023	1.358	1.054	1.289
2023-2024	0.710	0.921	0.771
Mean	1.070	1.005	1.065

Table 8 presents the measurement and decomposition of the water resource utilization efficiency change index by year and province. As shown in Table 8, Xinjiang recorded a 9.9% growth rate in water resource utilization efficiency during 2015-2024, the highest among all provincial-level administrative units. The average annual growth in water resource utilization efficiency exceeded 5% in Beijing, Hainan, Shanghai, Guangdong, Jiangsu, Zhejiang, Shandong, and other provinces, placing them at a relatively high national level. In these provinces, the contribution of the technological change index to water resource utilization efficiency is the largest, indicating that their efficiency improvements are mainly driven by technological progress. For example, in Beijing, Guangdong, and Jiangsu, the technological change index is significantly higher than the efficiency change index. By contrast, Tibet has a TFP index below 1, indicating a decline in water resource utilization efficiency. Both its technological change index and efficiency change index are close to 1, suggesting insufficient momentum for efficiency improvement.

Overall, technological progress is the main factor driving the improvement of water resource utilization efficiency in China. The modest increase in technical efficiency (management level) has provided some support for efficiency growth, but fluctuations in managerial efficiency in certain years and regions have constrained further improvements. In the future, it will be necessary to optimize management mechanisms and enhance the application of technology in order to achieve sustained and stable growth in water resource utilization efficiency.

Table 8. Decomposition of China's water resource utilization efficiency indices, 2015-2024

Region	TFP Index	Efficiency Change (EC)	Technological Change (TC)
Beijing	1.090	1.000	1.090
Guizhou	1.054	0.967	1.089
Sichuan	1.052	1.003	1.048
Hunan	1.084	1.019	1.064
Hainan	1.090	1.016	1.073
Shanghai	1.070	1.012	1.057
Shaanxi	1.069	0.99	1.079
Tibet	0.998	0.999	0.998
Jiangsu	1.062	1.007	1.055
Anhui	1.035	1.000	1.035
Liaoning	1.073	1.001	1.072
Fujian	1.082	1.009	1.073
Hubei	1.095	1.007	1.087
Zhejiang	1.082	1.017	1.064
Jilin	1.041	1.000	1.041
Henan	1.071	1.011	1.059
Ningxia	1.061	1.004	1.057
Guangdong	1.075	1.002	1.072
Inner Mongolia	1.054	1.000	1.054
Shanxi	1.066	1.008	1.058
Hebei	1.095	1.022	1.072
Yunnan	1.086	1.012	1.073
Xinjiang	1.099	1.023	1.074
Shandong	1.065	1.011	1.054
Tianjin	1.085	1.017	1.067
Jiangxi	1.095	1.011	1.083
Qinghai	1.055	0.988	1.067
Chongqing	1.084	1.011	1.072
Heilongjiang	1.064	0.988	1.077
Gansu	1.072	1.003	1.069
Guangxi	1.071	0.998	1.074
National	1.070	1.005	1.065

Note: Hong Kong, Macao, and Taiwan are excluded.

4. Discussion

4.1. Discussion of Results

By comparing the original and adjusted stages of the three-stage DEA within the DEA-Malmquist framework, it is found that after removing environmental factors and random disturbances, the efficiency values reflected in the third stage are closer to the true efficiency of water resource utilization. Eastern provincial-level regions such as Beijing, Shanghai, and Jiangsu maintain high efficiency indices in both the static three-stage DEA analysis and the dynamic Malmquist index analysis, which is consistent with the conclusion of Z. Zhang et al. that advanced technologies in the developed eastern region have served as a driving force for water resource utilization efficiency. But the present study, from the perspective of overall water resource utilization in China, finds that the modest improvement in technical efficiency (primarily management level) provides some support for efficiency growth, although fluctuations in managerial efficiency across some years and regions constrain further improvement. In the future, management mechanisms need to be optimized and technological application levels need to be enhanced so that the growth of water resource use efficiency can continue to improve.

4.2. Policy Recommendations

Based on the above empirical analysis, this study proposes the following policy recommendations. First, the industrial structure should be optimized to promote efficient water utilization. The eastern region should accelerate industrial transformation and upgrading and develop water-saving industries. The central region and major agricultural provinces should promote the dissemination of agricultural water-saving technologies to reduce redundant agricultural water use. The western region should rationally control the scale of high-water-consuming industries and develop distinctive water-saving agriculture and service industries.

Second, interregional technology diffusion should be strengthened to enhance the level of technological progress. A water-resource technology cooperation mechanism should be established between the eastern region and the central and western regions to promote advanced technologies such as water-saving irrigation and industrial water recycling. Technological investment in the western region should be increased to improve the technical foundation for water resource utilization.

Third, water resource management policies should be tailored to local conditions, with stronger monitoring and supervision. In water-abundant areas, quota-based management should be reinforced to avoid a “resource curse.” In provinces with severe managerial inefficiency, performance evaluation systems should be established to improve governance. In regions constrained by natural conditions, greater investment is needed in ecological water replenishment and water infrastructure. Meanwhile, a nationally unified monitoring network should be developed to strengthen dynamic supervision of industrial, agricultural, and domestic water use, while a joint water pollution prevention and control mechanism should be established to reduce pollutants such as NH_3-N and improve water recycling and reuse efficiency.

5. Conclusions

This study provides robust empirical evidence for improving efficiency evaluation and policy optimization in water resource utilization, while extending the practical applicability of the three-stage DEA and Malmquist index models. Using multidimensional provincial panel data from China, the results show that the three-stage DEA model effectively controls for environmental factors and random shocks, thereby yielding more reliable estimates of pure technical efficiency and scale efficiency. It also identifies province-specific efficiency gaps, such as those observed in Tibet and Ningxia. From a dynamic perspective, the Malmquist index reveals that changes in total factor productivity are mainly driven by technological progress, while technical efficiency change plays a comparatively smaller role. Evidence from provinces such as Beijing, Shanghai, and Jiangsu further illustrates substantial regional heterogeneity in the evolution of water use efficiency. By integrating static and dynamic analyses, this study offers a systematic understanding of current efficiency levels, temporal trends, and major constraints, thus providing a solid empirical basis for targeted policy intervention.

The findings further indicate that environmental conditions and random disturbances significantly influence efficiency evaluation. Compared with the traditional DEA approach, which tends to overestimate water resource utilization efficiency at both national and regional levels, the three-stage DEA model provides a more objective assessment of actual performance. Between 2015 and 2024, China's overall water resource utilization efficiency exhibited a fluctuating but upward trend, accompanied by pronounced regional disparities: efficiency was highest in the eastern region and lowest in the western region, although the regional gap gradually narrowed over time. Technological progress was the primary contributor to total factor productivity growth, whereas managerial inefficiency remained the main constraint on efficiency improvement in the central and western regions. In addition, per capita water availability and industrial structure exerted heterogeneous effects on the slack of different input factors.

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