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SPATIO TEMPORAL EVOLUTION AND INFLUENCING FACTORS OF WATER RESOURCE USE EFFICIENCY IN THE BEIJING–TIANJIN–HEBEI REGION: EVIDENCE FROM A SUPER EFFICIENCY SBM AND TOBIT MODEL

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Abstract: This study investigates the efficiency of water resource utilization in the Beijing–Tianjin–Hebei (BTH) region from 2013 to 2023. By employing a super-efficiency Slacks-Based Measure (SBM) model incorporating undesirable outputs, this research evaluated the spatial-temporal evolution of efficiency. Subsequently, a Tobit regression model was applied to analyze 13 determinants across natural, economic, social, and environmental dimensions. The results reveal that the region's efficiency followed a fluctuating trajectory characterized by phases of stability, growth, decline, and leveling off, with a mean value of 0.870. Significant spatial heterogeneity was observed, with Beijing and Tianjin exhibiting higher efficiency levels than Hebei. The Tobit analysis identified positive correlations with per-capita water resources, annual precipitation, per-capita GDP, the share of the tertiary industry, and water intensity, reflecting the influence of resource endowment, economic structure, and management capacity. Conversely, factors such as per-capita water use, the share of the primary industry, and insufficient scientific and technological investment exerted negative impacts, suggesting constraints related to redundant consumption and structural imbalances. Based on these findings, we recommend implementing differentiated regional management strategies, establishing a market-oriented agricultural water rights trading system, and creating an integrated BTH platform for the collaborative innovation and diffusion of water-saving technologies. These measures aim to foster sustainable resource utilization and high-quality regional development.
Keywords: Beijing–Tianjin–Hebei region; Water resource utilization efficiency; Super-SBM model; Tobit regression model; Influencing factors

1 INTRODUCTION

Water is a fundamental natural resource and a strategic economic asset vital to the national economy and public welfare. It also serves as a critical constraint on the ecological environment [1]. According to the 2024 "China Water Resources Bulletin", the national total water consumption has reached 5.928×10^{11} m^3, but the per capita comprehensive water consumption is only 421 m^3, highlighting a severe imbalance between water supply and demand. In terms of regional disparity, the Beijing - Tianjin - Hebei (BTH) region and other northern areas face significantly greater water scarcity than water-rich southern economic hubs like the Yangtze River Delta and the Pearl River Delta. Given that the BTH region is currently undergoing critical economic restructuring and a transition toward high-quality development, achieving efficient, scientific, and sustainable water utilization is urgent. Therefore, investigating the spatiotemporal evolution and determinants of water resource efficiency in the BTH region holds significant practical value for promoting resource conservation and meeting high-quality development goals.

Domestic and international literature on water resource efficiency has established a systematic framework encompassing methodological evolution, scale-specific empirical studies, and driver identification. Measurement approaches have progressed from simple single-factor ratios to total-factor evaluation models. While early single-factor methods were intuitive, they failed to capture the complexity of multi-input, multi-output systems. Consequently, Data Envelopment Analysis (DEA) has been widely adopted. Notably, the super-efficiency Slacks-Based Measure (SBM) distinguishes between efficient decision-making units (DMUs) and incorporates undesirable outputs, yielding more precise estimates [2]. Regional studies have deepened across spatial scales: Zheng et al. combines the Meta-frontier Super-SBM model and the Tobit model to analyze efficiency and factors influencing regional urban water resources utilization efficiency disparities across different technological frontiers [3]; Zhao et al. used the Super-SBM model to estimate water environmental governance efficiency for 283 prefecture-level cities in China over 2013–2022 and observed a shift from a dispersed spatial distribution to a multi-center agglomeration [4]. Analyses of determinants support policy design using tools such as the Theil index to measure regional disparity [5], the Malmquist index to decompose efficiency change [6], and Tobit regression to disentangle the complex drivers of performance [7].

In summary, existing studies provide a solid theoretical foundation but also leave gaps. Prior research often focuses either on efficiency measurement or on individual drivers, but rarely examines the coordinated multi-dimensional interplay of supply, structure, technology, and management needed to reveal the coexistence of promoting and inhibiting mechanisms. To address this gap, this study employs a slack-based measure (SBM) model that accounts for undesirable outputs to quantify BTH water-use efficiency, and uses Tobit regression to probe its determinants, aiming to inform policy for sustainable regional water management.

2 STUDY AREA, METHODOLOGY AND DATA SOURCES

2.1 Study Area

Located in the northern part of China's North China Plain, the BTH region spans approximately 216,000 km^2. Its topography exhibits distinct west-high-east-low characteristics, with mountains in the west and north and plains in the east. The region has a temperate monsoon climate, featuring major rivers such as the Haihe, Luanhe, and Yongding flowing along the terrain, and forming key water sources including Miyun Reservoir, Panjiakou Reservoir, and Baiyangdian Lake. However, the region has poor natural water endowment with low and uneven annual precipitation, mostly concentrated in the flood season [8]. According to 2023 data (from *China Statistical Yearbook 2024*), the total water resources in BTH amount to 3.0×10^{10} m^3, accounting for only 1.2% of the national total, with a per capita water resource of 274.4 m^3, less than one-sixth of the national per capita level. One of the core challenges facing the region is the long-term imbalance between development patterns and resource endowments, making water scarcity and irrational water use structure prominent bottlenecks restricting high-quality development, and revealing the complex coupling characteristics of water-economy-ecosystem [9]. Given its typicality and strategic importance, this study selects Beijing, Tianjin, and Hebei Province as research objects.

2.2 Methodology

2.2.1 SBM model incorporating undesirable outputs

The traditional DEA models, notably the CCR and BCC models, are radial and angular in nature and therefore fail to account for the effects of slack variables on water-use efficiency, often leading to efficiency overestimation for decision-making units (DMUs).Tone extended the SBM in 2003 to include undesirable outputs by placing slacks directly in the objective function [10]. This formulation resolves slackness issues and accommodates undesirable outputs, has been widely applied in ecological and environmental efficiency assessments, and substantially improves the accuracy of water-use efficiency estimation. The model is constructed as follows.

Assuming: $x \in R^{q}$, $\in R^{u_1}$, $y^b \in R^{u_2}$, define the matrices X、Y^g、Y^b, as follows:

$$
\begin{aligned}
X &= [x_1 \quad ,\cdots, \quad x_n] \in R^{q\times n} > 0\\
Y^g &= [y_1^g,\cdots, \quad y_n^g] \in R^{u_1\times n} > 0\\
Y^b &= [y_1^p,\cdots, \quad y_n^g] \in R^{u_2\times n} > 0
\end{aligned} \tag{1}
$$

A production possibility set P incorporating undesirable (non-desired) outputs can be constructed.

$$
\begin{gathered}
P = \{(x, y^g, y^b) | x \geqslant X\lambda, y^g \leqslant Y^g\lambda, y^b \geqslant \lambda, i \geqslant 0\}\\
\bar{x} \geqslant \sum_{i=1,\neq 0}^{n} \lambda_i x_i, \bar{y}^g \leqslant \sum_{i=1,\neq 0}^{n} \lambda_i y_i^g\\
\bar{y}^b \geqslant \sum_{i=1,\neq 0}^{n} \lambda_i y_i^b, \bar{x} \geqslant x_0, \bar{y}^g \leqslant y_0^g, \bar{y}^b \geqslant y_0^b\\
\bar{y}^g \geqslant 0, \lambda \geqslant 0\\
\rho = min \frac{\frac{1}{q}\sum_{i=1}^{q} \frac{\bar{x}_i}{x_{i0}}}{\frac{1}{u_1+u_2}\left(\sum_{r=1}^{u_1} \frac{\bar{y}_r^g}{y_{r0}^g} + \sum_{i=1}^{u_2} \frac{\bar{y}_1^b}{y_{10}^b}\right)}
\end{gathered} \tag{2}
$$

In the equations, x, y^g and y^b denote a decision-making unit's inputs, desirable (good) outputs, and undesirable (bad) outputs, respectively; s^-, s^g, and s^b are the slack vectors for inputs, desirable outputs, and undesirable outputs; λ is the weight vector; the subscript 0 refers to the unit under evaluation; and ρ (the objective value) is the efficiency score.

Although the SBM model with undesirable outputs improves efficiency assessment, it cannot further discriminate among multiple DMUs that attain an efficiency score of 1. To address this, the super-efficiency SBM (super-SBM) model applies additional treatment (e.g., excluding the evaluated DMU from the reference set) to rank the relative efficiency of previously efficient DMUs. Therefore, this study employs the super-efficiency SBM model to measure water-use efficiency; the model is constructed as follows.

Assume that in period t there are n decision-making units DMU_i. For each DMU_i, let x_i be the input vector, y_i^g the desirable (good) output vector, and y_i^b the undesirable (bad) output vector. Define matrices $X = [x_1, x_2, \ldots, x_n]$, $Y_i^g = [y_1^g, y_2^g, \ldots, y_n^g]$, and $Y_i^b = [y_1^b, y_2^b, \ldots, y_n^b]$. Assuming x_i, y_i^g and y_i^b are strictly positive, the functional form of the super-efficiency SBM model with undesirable outputs is given as follows:

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

$$s.t.\begin{cases} s_i^- \geqslant \sum_{j=1,\neq k}^{n} x_j\lambda_j + x_{ik}, i=1,2,\cdots,m \\ s_i^g \leqslant \sum_{j=1,\neq k}^{n} y_j^g\lambda_j - y_{ik}^g, i=1,2,\cdots,n_g \\ s_i^b \geqslant \sum_{j=1,\neq k}^{n} y_j^b\lambda_j - y_{ik}^b, i=1,2,\cdots,n_b \\ \sum_{j=1,\neq 0}^{n}\lambda_j = 1, \lambda\geqslant 0, y^g\geqslant 0, y^b\geqslant 0 \\ s_i^-\geqslant x_k, s_i^g\leqslant y_k^g, s_i^b\geqslant y_k^b \end{cases} \tag{3}$$

Here, ρ is the efficiency score estimated by the model for each DMU; s_i^-, s_i^g and s_i^b are the slack variables for DMU i's inputs, desirable outputs, and undesirable outputs, respectively; and λ is the weight vector.

2.2.2 The tobit model

Using DMU efficiency scores as the dependent variable and estimating them with standard OLS produces severely biased and inconsistent parameter estimates. The Tobit model, designed for limited/censored dependent variables, can effectively address this problem.

The Tobit model, proposed by Tobin [11], is a limited-dependent-variable model used for censored or truncated outcomes. By introducing a latent variable it converts the censored regression into a linear model, allowing consistent parameter estimation and avoiding the biases that ordinary least squares can produce. Given that water-use efficiency is nonnegative, the standard Tobit specification is:

$$\begin{gathered} y_i^* = \beta x_i + \mu_i \\ \mu_i \sim N(0,\sigma^2) \\ y_i = \begin{cases} y_i^*, y_i\geqslant 0 \\ 0, y_i < 0 \end{cases} \end{gathered} \tag{4}$$

Here, y_i^* denotes the latent (original) dependent variable; y_i the truncated (observed) dependent variable; x_i the vector of independent variables; β the vector of regression coefficients; and μ_i an independent, normally distributed error term.

2.3 Construction of the Indicator Framework and Data Sources

2.3.1 Input–output indicators

A scientifically grounded input–output indicator system is fundamental for accurately measuring urban water-resource efficiency. Drawing on the economic theory of production factors, the concept of water-resource efficiency, and previous studies, this paper classifies inputs into three categories—resources, labor, and capital—and explicitly accounts for industrial undesirable outputs to construct an evaluation framework tailored to the BTH region.

For input indicators, following Yin [12], resource input is measured by annual total water use. To analyze water-use structure, this is further decomposed into industrial, agricultural, domestic, and ecological water consumption. Labor input follows Deng et al [13], and is proxied by employment counts in the primary, secondary, and tertiary sectors. Capital input is proxied by total fixed-asset investment in the period, capturing the flow of physical capital in regional economic development [14].

For outputs, the desirable output is measured by regional GDP to capture positive economic benefits, while the undesirable output is proxied by chemical oxygen demand (COD) emissions. Detailed definitions of the indicators are presented in Table 1.

Table 1 Input–Output Indicator System

Indicator type	Criterion	Definition / Unit	Reference
Input indicators	Resource input	Industrial water use (100 million m^3) Agricultural water use (100 million m^3) Domestic water use (100 million m^3) Ecological water use (100 million m^3)	[12]
	Productivity input	Employment by three	[13]

Indicator type	Criterion	Definition / Unit	Reference
		sectors (10,000 persons)	
	Human capital input	Total fixed-asset investment (100 million CNY)	
Output indicators	Desirable outputs	Regional GDP (100 million CNY)	[14]
	Undesirable outputs	COD emissions (10,000 tonnes)	

2.3.2 Determinants

The spatiotemporal variation in water-use efficiency arises from the interplay of natural background, economic development, social structure, and environmental policy. To systematically analyze the key drivers and constraints in the BTH region, and based on a review of relevant studies, we adopt a systems approach that classifies determinants into three dimensions—natural, economic and social—and construct an indicator framework (Table 2) to comprehensively reveal their internal pathways and mechanisms.

(1) Natural dimension: resource endowment is the foundational condition. Natural factors constitute the physical basis of water supply and demand. This study selects per-capita water resources, annual precipitation, and per-capita water use as core indicators of resource endowment. Generally, richer natural water endowments are often associated with lower water-use efficiency—the "resource curse" can shape production and consumption patterns and water-management attitudes [15].

(2) Economic dimension: development pattern and structure as core drivers. Economic development level and industrial structure directly determine water-consumption intensity and utilization patterns. We use GDP per capita to measure regional economic development and, drawing on the environmental Kuznets curve theory, examine possible nonlinear relationships between efficiency and growth. We also include the GDP shares of the primary, secondary, and tertiary sectors to capture the optimizing effect of industrial upgrading on water-use efficiency [16].

(3) Social dimension: population agglomeration and intellectual support as long-term foundations. Social factors—population distribution, human capital, and technological innovation—profoundly shape water-management capacity and use patterns. We use water consumption per RMB10,000 of GDP, urbanization rate, and population density to capture spatial agglomeration; urbanization may generate scale effects that improve supply efficiency but can also intensify local water stress. The shares of education expenditure and of science & technology investment measure societal commitment to human capital and innovation, which directly affect the development, diffusion, and application of water-saving technologies and thus provide intrinsic drivers for improving water-use efficiency [17].

(4) Environmental dimension: governance investment and pollution control as constraint boundaries. The environmental dimension reflects societal responses and governance efforts addressing water environment issues. This study selects the proportion of environmental protection investment in GDP to characterize the government's emphasis and financial support for environmental governance, which directly affects the construction and operation effectiveness of pollution treatment facilities [18].

Table 2 Indicator System of Influencing Factors

Indicator layer	Criterion layer	Measurement layer (unit)	Reference
Natural	Water resource endowment	Per-capita water resources (m^3/person) Annual precipitation (m^3) Per-capita water use (m^3//person))	[15]
Economic	Economic development level	Per-capita GDP (10,000 CNY/person)	
	Industrial structure	Primary industry GDP share (%) Secondary industry GDP share (%) Tertiary industry GDP share (%)	[16]
Social	Water intensity	Water use per 10,000 CNY GDP (m^3/10k CNY)	
	Degree of spatial agglomeration	Population density (persons/km^2)	
	Urbanization level	Urban population share of total population (%)	[17]
	Education investment level	Education expenditure as share of total expenditure (%)	
	Science & technology investment level	Science & technology expenditure as share of total expenditure (%)	
Environment	Environmental protection investment level	Environmental protection expenditure as share of total expenditure (%)	[18]

2.4 Data Sources

All data in this study, including input indicators, output indicators, and influencing factor indicators, are sourced from the *China Statistical Yearbook*, *Hebei Statistical Yearbook*, *Beijing Statistical Yearbook*, *Tianjin Statistical Yearbook* (2014–2024), *Water Resources Bulletins* (2013–2023), and other relevant literature. For statistical issues, missing data for specific regions/periods were supplemented using linear interpolation.

3 MEASUREMENT OF WATER-RESOURCE EFFICIENCY AND ANALYSIS OF ITS SPATIO-TEMPORAL EVOLUTION

The study divides the research area into three units: Beijing, Tianjin, and Hebei, to measure and analyze water use efficiency separately. Using the non-radial, non-oriented super-efficiency SBM model on the DEArun software platform, we evaluated the water use efficiency of the BTH region from 2013 to 2023, and visualized its spatiotemporal evolution characteristics with the help of ArcGIS tools.

Table 3 Water-Resource Utilization Efficiency by Province and Municipality in the BTH Region, 2013-2023

Province	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023	Mean
Beijing	1.023	1.004	1.008	1.009	1.055	1.015	1.017	1.019	1.009	1.122	1.030	1.028
Tianjin	1.249	1.013	1.008	1.055	1.020	1.021	1.077	1.032	1.013	1.015	1.038	1.049
Hebei	1.009	0.790	1.026	1.023	0.749	0.249	0.224	0.195	0.191	0.197	0.196	0.532
Mean	1.093	0.935	1.014	1.029	0.941	0.762	0.773	0.748	0.738	0.778	0.755	0.870

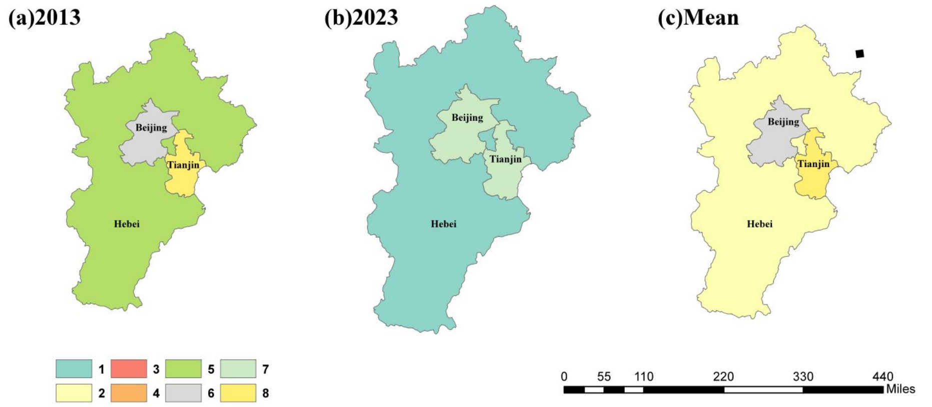

Figure 1 Comparison of Water-Resource Efficiency in the BTH Region for 2013, 2023, and the 2013－2023 Mean (Efficiency Increased from 1 to 8)

Table 3 and Figure 1 indicate that from 2013 to 2023 the BTH region's water-use efficiency exhibited an overall pattern of "stable → rise → decline → eventual low-level stabilization." The mean efficiency was 0.870, well below the effective level, indicating overall inefficiency and that water resources have not yet been used intensively and efficiently in production. Over time, aggregate efficiency fell from 1.094 in 2013 to 0.755 in 2023, with an average annual contraction rate of 3.39%, reflecting a fluctuating downward trajectory. This trend suggests that, despite ongoing industrial upgrading, capacity elimination, increased technological investment, and talent attraction, these measures have not yet produced substantive improvements in water-use efficiency; considerable scope for improvement remains [19].

By stage, efficiency was highest in 2013; it rose rapidly from 2014 to 2016, peaking at 1.029 in 2016; then fell sharply in 2018 and remained at a low level of about 0.759 from 2018 to 2023. This trajectory reflects the combined effects of national policies, industrial restructuring, and natural-condition variability. Specifically, the 2013 peak benefited from the cumulative effects of the 2011 national decision to accelerate water-conserving reforms, structural optimization in the region (e.g., a higher services share in Beijing and tighter controls on high-consumption projects in Tianjin Binhai New Area), and above-average precipitation. The 2014–2016 rise and 2016 peak were driven by implementation of the Outline of the BTH Coordinated Development Plan, the establishment of cross-regional unified water-resource management, water supply from the Middle Route of the South-to-North Water Diversion Project, and policy measures such as stepped water pricing and water-use quotas from water-saving pilots. The slight downturn in 2017 was associated with a surge in infrastructure water use during the initial construction of Xiong'an New Area and below-average rainfall [20]. The 2018 collapse mainly reflected reduced industrial water efficiency during Hebei's capacity-reduction campaign, lower emergency water-use efficiency after closure of self-supplied wells during groundwater remediation, and urban demand peaks from extreme summer weather. The prolonged weakness from 2019–2023 is linked to uneven cross-regional policy implementation, increased demand from major events (e.g., snowmaking for the Winter Olympics), and routine ecological water replenishment competing with production use.

The analysis indicates that policy and regulatory guidance, natural-condition variability, and short-term pressures associated with economic structural transformation jointly shaped the fluctuating trajectory of water-use efficiency in the BTH region.

4 ANALYSIS OF INFLUENCING FACTORS

To further elucidate the drivers of the estimated water- use efficiency in the BTH region, this study performed panel Tobit regression analysis in Stata 18.0; the results are reported in Table 4.

Table 4 Tobit Regression Results for Key Determinants of Water-Resource Efficiency in the BTH Region

Criterion	Explanatory variable	Coefficient	Standard error	*z value*	*P value*
Water resource endowment	Per-capita water resources	1.104×10^{-4}	3.850×10^{-4}	0.290	0.774
	Annual precipitation	-9.952×10^{-4}	3.645×10^{-3}	-0.270	0.785
	Per-capita water use	1.604×10^{-4}	2.876×10^{-4}	0.560	0.577
Economic development level	Per-capita GDP	3.210×10^{-6}	1.860×10^{-6}	1.720	0.085
Industrial structure	Primary industry GDP share	-17.384^{**}	8.278	-2.100	0.036
	Secondary industry GDP share	0.390	1.006	0.390	0.698
	Tertiary industry GDP share	0.000	0.000	0.000	0.000
Water intensity	Water use per 10,000 CNY GDP	0.048^{***}	0.014	3.300	0.001
Degree of spatial agglomeration	Population density	1.332	2.633	0.510	0.613
Urbanization level	Urban population share of total populatio	-2.420	8.133	-0.300	0.766
Education investment level	Education expenditure as share of total expenditure	1.983	4.140	0.480	0.632
Science & technology investment level	Science & technology expenditure as share of total expenditur	-3.850×10^{-5}	4.650×10^{-5}	-0.830	0.408
Environmental protection investment level	Environmental protection expenditure as share of total expenditure	-0.296	2.196	-0.130	0.893
	Constant	-1.706	3.669	-0.460	0.642

Note: ***, ** denote significance at the 1% and 5% levels, respectively.

Based on the regression results for the primary determinants reported in Table 4, the detailed analysis is as follows.

The Tobit results indicate that some factors promote water-use efficiency in the BTH region. Water use per 10,000 CNY of GDP is negative and statistically significant at the 1% level, confirming that reductions in this core water-intensity indicator are a key manifestation of improved water-use efficiency. Other variables (e.g., annual precipitation, per-capita GDP) have positive coefficients but are not statistically significant; their effects remain inconclusive, possibly due to limited sample size, endogeneity, or regional heterogeneity. Overall, lowering water use per 10,000 CNY GDP is the most direct and statistically robust pathway to raise regional water-use efficiency, achievable through technological upgrades and strengthened water-management practices to foster efficiency-driven intensive development.

Among the inhibitory factors, the share of the primary industry is significantly negative (coefficient = -17.384, $p < 0.05$), indicating a robust adverse relationship with water-use efficiency and reflecting agriculture's still-large share of water consumption that structurally constrains overall efficiency. Other variables (e.g., per-capita water use, R&D/technology investment) have negative coefficients but are not statistically significant, so their suppressive effects remain inconclusive. Hence, an excessively high primary-industry share is the key shortcoming hindering efficiency improvements; advancing agricultural water-saving modernization and optimizing the three-sector structure should be priority responses.

5 DISCUSSION

This study makes two key contributions: methodologically, it integrates a super-efficiency SBM model with undesirable outputs and Tobit regression to provide a holistic evaluation of water resource utilization efficiency, addressing the limitations of conventional DEA models by distinguishing efficient decision-making units and accounting for environmental costs. Substantively, it pioneers a four-dimensional analytical framework (natural, economic, social, and environmental) to dissect the determinants of water efficiency, revealing a "double-edged mechanism" where factors like per capita GDP and tertiary industry share synergistically promote efficiency, while primary industry share and insufficient R&D investment impose structural constraints. A primary limitation is the omission of intra-regional variations: the provincial-level analysis masks disparities within sub-region, which could be addressed by incorporating prefecture-level data to capture localized efficiency dynamics.

6 CONCLUSIONS AND RECOMMENDATIONS

This study employs a super-efficiency SBM model to measure water resource efficiency in the BTH region from 2013 to 2023. The results indicate an overall trend of "initial stability, followed by an increase, subsequent decrease, and final stabilization at a low level." The average water resource utilization efficiency is 0.870, significantly below the effective level, indicating an overall non-effective state. The water resource utilization efficiency of Beijing and Tianjin is generally higher than that of Hebei Province, suggesting that there is still room for improvement in the overall water resource utilization efficiency of the BTH region. In-depth analysis of efficiency causes is conducted by applying Tobit regression to analyze 13 refined factor indicators across four dimensions: natural, economic, social, and environmental. The results show that per capita water resources, annual precipitation, per capita GDP, the proportion of the secondary industry, the proportion of the tertiary industry, water consumption per 10,000 yuan of GDP, education investment level, and urbanization degree can significantly promote the improvement of water resource utilization efficiency in the BTH region. In contrast, per capita water consumption, the proportion of the primary industry, scientific and technological investment level, population density, and environmental protection investment level have an inhibitory effect on water resource utilization efficiency in the region. Based on the above research conclusions, in order to improve the water resource utilization efficiency of the BTH region and achieve high-quality regional economic development, the following suggestions are put forward.

(1) Establish a differentiated assessment system and implement regionally targeted management. This study confirms that reducing water use per 10,000 CNY GDP is the most direct and significant pathway to improve regional water-use efficiency. Therefore, it is recommended to include its reduction rate as a key mandatory indicator in the BTH coordinated development assessment. Based on the industrial bases and water-use structures of the three regions, differentiated target management should be implemented: Beijing and Tianjin should focus on improving water-saving efficiency in high-tech industries and modern services; Hebei should prioritize assessing the reduction in water intensity after upgrading traditional industries such as steel and chemicals, thereby decomposing macro-efficiency goals into quantifiable micro-management actions.

(2) Establish a market-based agricultural water-rights trading mechanism to drive structural optimization via economic incentives. Tobit results show an excessively high primary-sector share is a key structural constraint on water-use efficiency. Pilot a “conservation-to-rights” conversion in major agricultural water users (e.g., Hebei): finance agricultural water-saving upgrades, certify saved water as tradable entitlements, and permit paid transfers to industrial or ecological users in Beijing and Tianjin. This both internalizes incentives for agricultural water saving and, through market allocation, shifts water from low-productivity to higher-productivity uses, fundamentally optimizing regional water-use structure.

(3) Establish an integrated BTH collaborative platform for water-saving technology innovation and promotion. Ultimately, improvements in water-use efficiency depend on technological progress and widespread application. It is recommended that the governments of the three regions jointly take the lead in regularly releasing a catalog of water-saving technologies for key industries in BTH, and recommend the implementation of mature and reliable water-saving technologies in the catalog for new construction and renovation projects. At the same time, a regional collaborative innovation fund should be established to support the formation of a "Water-Saving Technology Alliance" composed of scientific research institutions in Beijing and Tianjin and industrial parks in Hebei, to carry out joint research on common high water-consuming links, and ensure that advanced water-saving technologies can be implemented and transformed to produce practical results.

COMPETING INTERESTS

The authors have no relevant financial or non-financial interests to disclose.

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