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Virtual Water Resource Utilization Efficiency and Influencing Factors in China's Tertiary Industry: An Input-Output and Stochastic Frontier Analysis

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Abstract

This study aims to investigate the virtual water utilization efficiency and its influencing factors across 14 industries of China's tertiary industry during 2002-2020. By applying the input-output model, Shephard water distance function, and stochastic frontier analysis (SFA), this research incorporates multi-factor analysis with the total virtual water footprint as the water input indicator. Results show that the annual total virtual water footprint of the tertiary industry exhibited fluctuating changes, influenced by macroeconomic conditions, industrial structure, and water-saving policies. The overall virtual water utilization efficiency increased, though the growth rate decelerated, with significant disparities across industries: high-efficiency industries were concentrated in specific fields, while low-efficiency industries were mostly traditional service industries. Stochastic frontier analysis indicates that most estimation errors originated from the technical inefficiency term. Technical inefficiency analysis reveals that factors such as water resource endowment are significantly correlated with water-related technical inefficiency. This study provides a basis for deepening the understanding of water resource utilization in the tertiary industry and offers references for optimizing water resource management policies.

Keywords: virtual water utilization efficiency; Input-output model; Shephard energy distance function; Stochastic frontier analysis

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Introduction

Water is the source of life and plays a crucial role in economic and social development. With rapid global economic growth and continuous population expansion, water scarcity has become an increasingly severe issue, serving as a key constraint on national development (Qian et al., 2011). As a country with relatively limited water resources, China's per capita water availability is far below the global average, exacerbating water supply-demand conflicts. In this context, improving water resource utilization efficiency has emerged as a critical measure to alleviate water stress and achieve sustainable development (Sun & Zhao, 2014). Among various industries, the tertiary industry is vital for optimizing economic structures, promoting employment, and driving economic growth (Yang, 2018). In recent years, China's tertiary industry has witnessed a steady increase in its GDP share, accompanied by expanding water consumption. However, research on water resource utilization efficiency in the tertiary industry remains insufficient, failing to meet the needs of precise water management (Huang et al., 2022). Therefore, investigating the water resource utilization efficiency of the tertiary industry and its influencing factors is of significant practical importance for rational water allocation and sustainable development of the sector.

Scholars worldwide have conducted extensive research on water resource utilization efficiency. Early studies primarily employed single-factor indicators (Mo et al., 2004; Li et al., 2008), such as water consumption per unit of output, which are simple and intuitive but unable to comprehensively reflect the overall efficiency of water use. Subsequently, data envelopment analysis (DEA) gained popularity due to its advantages in handling multi-input and multi-output problems without predefined production functions. Many scholars have applied DEA and its extended models to measure and analyze water resource utilization efficiency across different regions and industries (He et al., 2017; Molinos et al., 2016; Cheng et al., 2016; Hu et al., 2018; Deng, 2019; Adler, N., Friedman, L., & Sinuany-Stern, Z. 2002). However, DEA has limitations, including its inability to account for random factors and statistical noise, as well as its lack of direct analysis of technical efficiency determinants (Chambers et al., 1998).

To address these issues, stochastic frontier analysis (SFA) based on the Shephard distance function has increasingly drawn attention (Wang & Li, 2021; Yang, 2012; Wang & Dong, 2024; Chen & Liu, 2022; Xing et al., 2018). This method not only measures efficiency and analyzes influencing factors simultaneously but also incorporates the impact of randomness on outputs, yielding more scientific and reliable results (Li & Fan, 2009). In terms of research perspectives, previous studies often focused on physical water consumption, whereas the concept of virtual water has opened new avenues for water resource research (Hoekstra & Hung, 2003). Virtual water refers to "invisible" water embedded in goods and services. Analyzing water resource efficiency from the virtual water perspective allows for comprehensive consideration of both direct and indirect water use across industries, providing a more holistic understanding of actual water utilization (Sun et al., 2025; Cai et al., 2020; Wu et al., 2022). Although some studies have adopted this perspective, research specifically targeting the tertiary industry remains underdeveloped (Zhang et al., 2010).

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This study aims to fill this gap by examining China's tertiary industry. Using input-output models, the Shephard water distance function, and stochastic frontier analysis (SFA), we investigate the virtual water utilization efficiency and its determinants across 14 industries of the tertiary industry from 2002 to 2020. We construct a comprehensive analytical framework by treating total virtual water footprint as the water input indicator and integrating multiple factors, including labor, capital, technological R&D, pollution control, and subsector value added as the output. Through systematic analysis of trends in virtual water footprints, dynamic evolution of virtual water utilization efficiency, and key efficiency determinants, this research provides a scientific basis for formulating targeted water management policies and promoting efficient water use in the tertiary industry.

Methods

Input-output model construction

Compilation of the Water Resources Input - Output Table

Using the merged sectoral input - output table, the water - use data of each sector are taken as the water - related inputs and outputs to compile the water resources input - output table (Table 1). The direct consumption coefficient matrix can be calculated from the input - output table (Leontief & Ford, 1970):

$$A=\begin{pmatrix} a_{11} & \cdots & a_{1n} \\ \vdots & \ddots & \vdots \\ a_{n1} & \cdots & a_{nn} \end{pmatrix}, \text{ where } a_{ij}=\frac{x_{ij}}{X_j}$$

Virtual Water Accounting

(1) The direct water - use coefficient reflects the direct water - use intensity of sector *i*, representing the amount of water resources directly consumed by sector *i* for each unit of total output produced (Xu et al., 2002). The calculation formula is as follows:

$$w_i=\frac{W_i}{X_i},\quad i=1,2,\cdots,n$$

By calculating the direct water - use coefficients of all sectors, we can obtain the row matrix of direct water - use coefficients:

$$DWC=[w_1,w_2,w_3,\cdots,w_n].$$

(2) The total water - use coefficient reflects the total water - use intensity of sector *i*, representing the sum of direct and indirect water consumption for each unit of total output produced by sector *i* (Xu et al., 2002). The import part needs to be excluded during the calculation:

$$B=\begin{pmatrix} a_1 & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & a_n \end{pmatrix}, \text{ where } a_i=\frac{X_i}{IM_i+X_i}$$

By calculating the total water - use coefficients of all sectors, the row matrix of total water - use coefficients can be obtained, where DWC is the matrix of direct water - use coefficients, I is the identity matrix, B is the diagonal matrix of domestic production proportion, and A is the direct consumption coefficient matrix.

(3) The formula for calculating the virtual water of each sector is as follows:

$$TW=TWC\cdot TFU$$

In the formula: TWC is the row matrix of total water - use coefficients, TFU is the column matrix composed of the total final use of each sector in the input - output table, and TW is the matrix composed of the virtual water footprints consumed by each sector.

Table 1 Input-Output Table

	Intermediate Use			Final Use			Import	Total Output
	Sector 1	…	Sector n	Final Consumption Expenditure	Export	Total Final Use		
Sector 1	x_{11}	…	x_{1n}	TC_1	EX_1	TFU_1	IM_1	X_1
…	…	…	…	…	…	…	…	…
Sector n	x_{n1}	…	x_{nn}	TC_n	EX_n	TFU_n	IM_n	X_n
Value Added	V_1	…	V_n					
Total Input	X_1	…	X_n					
Water	W_1	…	W_n					

Shephard Water Resource Distance Function

Before constructing the distance function, a production technology set must first be defined. Based on the original three - factor framework (capital, labor, and personnel), two additional indicators are incorporated: technological R&D investment and pollution control investment. Thus, the input factors include capital input (K), labor (L), water resources (W), technological R&D (R), and pollution control (S), with sectoral value added as the output factor. The production technology set is expressed as:

$$(P=\{(K,L,W,R,S,Y):(K,L,W,R,S)\text{ can produce }Y\}$$

Following Zhou et al.'s construction of the Shephard energy distance function (Zhou et al., 2012), the Shephard water resource distance function is defined as:

$$D_e(K,L,W,R,S,Y)=\sup\{\alpha:(K,L,\frac{W}{\alpha},R,S)\in P(K,L,W,R,S,Y)\}$$

In the formula: *P (K, L, W, R, S, Y)* represents the possible set of outputs that can be produced under the input combination of capital (K), labor (L), water resources (W), technological R & D (R), and pollution control (S) under certain production technology conditions. The distance function D_e represents the maximum contraction ratio α of water resource input while keeping the output unchanged.

According to this definition, W/D_e is expressed as the optimal water resource input; the ratio of the optimal water resource input to the actual input is expressed as the water resource utilization efficiency *TWE*. Therefore, the formula is expressed as follows:

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$$TWE = \frac{\frac{W}{D_e(K,L,W,R,S,Y)}}{W} = \frac{1}{D_e(K,L,W,R,S,Y)}$$

When $D_e(K, L, W, R, S, Y) = 1$, it means that it is currently on the production frontier, and the water resource utilization efficiency at this time is 1.

Construction of the Stochastic Frontier Model

In terms of the selection of the functional model, since the Cobb - Douglas production function has relatively more limitations and less flexibility (Battese & Broca, 1997), this paper adopts the trans - log production function in the selection of the functional form:

$$\ln D_e(K_{it},L_{it},W_{it},R_{it},S_{it},Y_{it}) = \beta_0 + \sum_{j\in\{K,L,W,R,S,Y\}} \beta_j \ln X_{jit} + \beta_t t + \sum_{j\in\{K,L,W,R,S,Y\}} \beta_{jj}(\ln X_{jit})^2 + \beta_{tt}t^2 + \sum_{j<k,j,k\in\{K,L,W,R,S,Y\}} \beta_{jk} \ln X_{jit} \ln X_{kit} + \sum_{j\in\{K,L,W,R,S,Y\}} \beta_{jt} t \ln X_{jit} + v_{it}$$

Here, X_{jit} represents the input variable corresponding to j (for example, when $j = K$, $X_{Kit} = K_{it}$, and so on). In the formula: i represents the industry; t represents the year.

K_{it}, L_{it}, W_{it}, R_{it}, S_{it}, and Y_{it} respectively represent the fixed assets, the number of employees, the virtual water consumption, the technological R & D investment, the pollution control investment, and the added value of industry i in year t; v_{it} is the random error term, which follows the standard normal distribution; β is the parameter to be estimated. Through the deformation and derivation of the formula, the stochastic frontier function model in the standard form can be obtained:

$$\ln \frac{1}{W_{it}} = \beta_0 + \sum_{j\in\{K,L,R,S,Y\}} \beta_j \ln X_{jit} + \beta_t t + \sum_{j\in\{K,L,R,S,Y\}} \beta_{jj}(\ln X_{jit})^2 + \beta_{tt}t^2 + \sum_{j<k,j,k\in\{K,L,R,S,Y\}} \beta_{jk} \ln X_{jit} \ln X_{kit} + \sum_{j\in\{K,L,R,S,Y\}} \beta_{jt} t \ln X_{jit} + v_{it} - u_{it}$$

Here, X_{jit} represents the input variable correspond-ing to j (for example, when $j = K$, $X_{Kit} = K_{it}$, and so on). $u_{it} = lnD_e(K_{it}, L_{it}, W_{it}, R_{it}, S_{it}, Y_{it})$ re-presents the water resource inefficiency term of industry i in year t, and it follows the truncated normal distribution $N(m_{it}, \sigma_{it}^2)$; $(v_{it} - u_{it})$ represents the composite error term. Explanatory variables are introduced for the water resource inefficiency term: environmental protection investment (EPI), water resource endowment (WRE), technological development level (TDL), education development level (EDL), industrial structure (IS), urbanization process (UP), economic development level (PG), and industry endowment (IE). At this time, the water resource inefficiency function is:

$$m_{it} = a_0 + a_1 EPI + a_2 WRE + a_3 TDL + a_4 EDL + a_5 IS + a_6 UP + a_7 PG + a_8 IE + w_{it}$$

Among them, W_{it} is the random disturbance term of the water resource inefficiency function, and α_i is the estimated parameter. According to the setting of the technical inefficiency term by Battese and Corra (Battese & Corra, 1977), let $\gamma = \frac{\sigma_u^2}{\sigma_v^2 + \sigma_u^2}$, which represents the proportion of the water resource inefficiency term in the composite error term. The closer the ratio is to 1, the greater the influence proportion of the water resource inefficiency term.

Data Sources and Variable Descriptions

This study uses China's Input-Output Tables (2002, 2007, 2010, 2012, 2015, 2020) to integrate sectors into 19 industries per GB/T 4754-2017, selecting 14 tertiary sectors as decision units, Specific sector names and their codes are shown in Table 2. Panel data across 8 years explore their 2002-2020 water efficiency and influences. Water use data from China Water Resources Bulletin are determined by the "water production and supply" input proportions in Input-Output Tables. Tertiary industry water use is calculated by subtracting urban household water from total urban domestic water, reflecting public service consumption. Relevant literature informs the selection of input-output and influencing variables for efficiency analysis.

Table 2 Sectors and Their Codes

Code	Industry	Code	Industry	Code	Industry
01	Wholesale and Retail Trades	06	Real Estate Industry	11	Education
02	Transportation, Storage and Post Industry	07	Leasing and Business Services	12	Health Care and Social Work
03	Accommodation and Catering Services	08	Scientific Research and Technical Services	13	Culture, Sports and Entertainment Industry
04	Information Transmission, Software and Information Technology Services	09	Water Conservancy, Environment and Public Facilities Management Industry	14	Public Administration, Social Security and Social Organizations
05	Financial Industry	10	Resident Services, Repair and Other Services		

Input - Output Variable System

In this section, an input-output indicator system covering six dimensions is constructed to comprehensively reflect the multi-factor driving relationships of virtual water resource utilization efficiency. The input-output model is used to quantify the correlation mechanisms among variables, providing data support for subsequent efficiency calculations. Specific indicator data, their sources, and explanations are presented in Table 3.

Table 3 Data Sources and Explanations for Input-Output Variables

Variable	Indicator Definition	Data Source	Explanation
Water Resource Input	Total Virtual Water Footprint	China Statistical Yearbook and China Water Resources Bulletins	Calculated based on the input - output model
Labor Input	Number of Employees	China Statistical Yearbook	Reflects the scale of labor factors
Capital Input	Investment in Fixed Assets	China Statistical Yearbook	Reflects the accumulation of physical capital
Technological R&D	Expenditure on R&D	Industry statistical data and Science and	Represents the intensity of investment in

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Input		Technology Statistical Yearbook	technological innovation
Pollution Control Input	Total Pollution Control Funds	China Environmental Statistical Yearbook	Measures the scale of environmental cost investment
Economic Output	Industry Added Value	China Statistical Yearbook	Reflects the final results of production activities

Influencing Factor Variable System

In this section, eight key socio-economic variables are selected to systematically analyze their mechanisms of action on water resource utilization efficiency. Through the construction of multi-dimensional indicators, the comprehensive impacts of factors such as regional differences, structural characteristics, and policy orientations are revealed. Specific indicator data, their sources, and explanations are presented in Table 4.

Table 4 Influencing Factor Variables: Data Sources and Explanations

Variable	Indicator Definition	Data Source	Explanation
Water Resource Endowment	Per Capita Water Resources	China Water Resources Bulletins	Reflects the constraints of natural conditions
Industrial Structure	Proportion of Tertiary Industry Output Value in GDP	China Statistical Yearbook	Reflects the degree of optimization of the economic structure
Industry Endowment	Ratio of Added Value to the Number of Employees	Industry statistical data	Determines the technology - or labor - intensive nature of the industry
Urbanization Process	Proportion of Urban Population in the Total Population	China Statistical Yearbook	Measures the stage of social development
Economic Development Level	Per Capita GDP	Provincial statistical year books	Reflects the characteristics of the economic development stage
Scientific and Technological Development	Number of Patent Applications Accepted	Website of the National Bureau of Statistics	Represents the technological innovation ability
Education Development	Number of University Graduates	Website of the National Bureau of Statistics	Reflects the accumulation of human capital
Degree of Environmental Protection Investment	Proportion of Environmental Protection Investment in GDP	China Environmental Statistical Yearbook	Reflects the intensity of investment in environmental governance

Results Analysis

Analysis of Sectoral Virtual Water Footprint Measurement Results

Based on calculations from the input-output model, the annual total virtual water footprint and its growth rate for the 14 sectors in China's tertiary industry during the period from 2002 to 2020 are presented in Figure 1, while the multi-year averages and annual growth rates of sectoral virtual water footprints are shown in Figure 2.

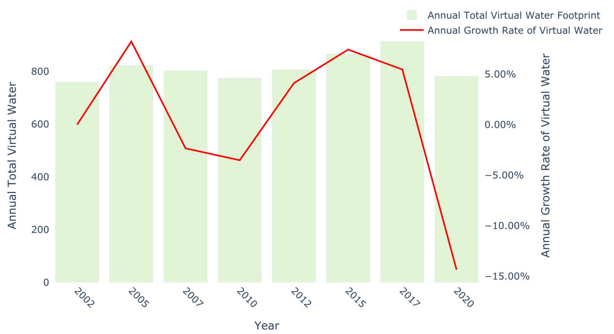

Figure 1 Annual Total Virtual Water Footprint and Growth Rate Trend Chart

Figure 1 reveals that the annual total virtual water footprint exhibits significant fluctuating characteristics across different years: it showed a continuous upward trend from 2002 to 2005, increasing from 759.449127 billion m³ to 821.94952 billion m³, with a growth rate of 8.23%. This period coincided with a high-speed economic expansion in China, where the average annual GDP growth rate exceeded 10%. The accelerated processes of industrialization and urbanization directly drove up water demand. A downward trend was observed from 2005 to 2010, followed by a resurgence from 2010 to 2015, and a new round of decline from 2015 to 2020.

Such cyclical fluctuations are closely linked to macroeconomic cycles, industrial structure evolution, and advancements in water resource management technologies. After 2005, the promotion of water-saving technologies and improvements in production efficiency reduced the intensity of water consumption in high-water-use sectors. With the gradual recovery of the global economy from the financial crisis in 2010, the rapid expansion of domestic service industries once again increased water demand. Since 2015, the deepening of supply-side structural reforms has shifted the industrial structure toward low-water-consumption and high-value-added sectors. The elimination of outdated production capacity and the popularization of green production technologies effectively curbed the growth of virtual water footprints.

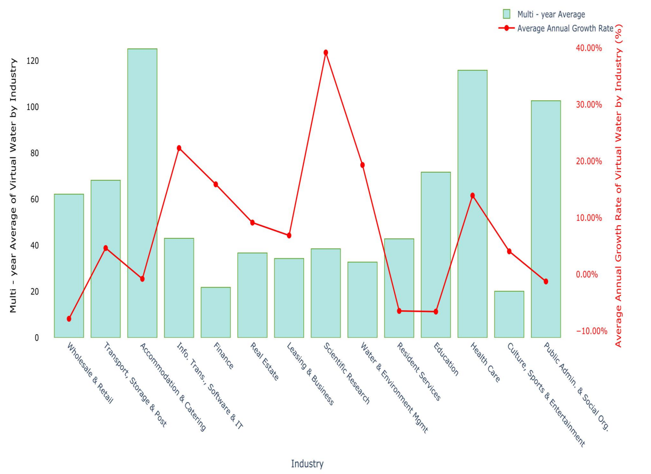

Figure 2 Trend Chart of Multi-year Average and Average Annual Growth Rate of Virtual Water

The data indicate a significant interactive relationship between water demand characteristics in different economic growth stages, improvements in production technical efficiency, and industrial structure optimization. The early high-speed growth was

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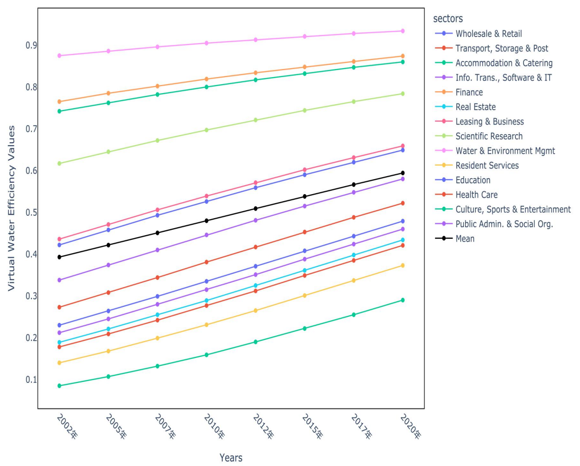
accompanied by a synchronous increase in water demand, while in later stages, technological progress and industrial restructuring gradually enhanced water resource utilization efficiency, driving the total virtual water footprint into a downward trajectory.An analysis of the multi-year averages of sectoral virtual water consumption in Figure 2 shows that the accommodation and catering services, education, culture, sports and entertainment, and public administration and social organization sectors exhibit relatively high values. This is likely due to their intensive involvement in infrastructure construction and daily operational water use—such as water for catering services, daily water consumption in schools, and water for operating cultural and sports venues. In contrast, the financial industry, health care, social security, and social welfare sectors have lower multi-year average virtual water consumption, which is related to their service- and office-oriented nature with fewer physical water-consuming links.

Regarding the average annual growth rates of sectoral virtual water consumption: industries such as scientific research and technical services, information transmission, computer services, and software show relatively high growth rates. In recent years, these sectors have developed rapidly with expanding scales, and activities such as cooling for big data centers and the expansion of office spaces have increased water demand. Conversely, sectors like wholesale and retail trade, resident services and other services, and education have negative average annual growth rates. This is speculated to result from continuous optimization of water management and improvements in water use efficiency within these industries, as well as reduced water demand influenced by factors such as industrial restructuring and changing market environments.



Analysis of Virtual Water Resource Utilization Efficiency Measurement Results

Using StataMP software, the virtual water resource utilization efficiency values for 14 sectors in the tertiary industry across multiple years from 2002 to 2020 were calculated, along with the multi-year averages for each sector and the annual average across all sectors, as shown in Table 5.

From 2002 to 2020, the overall virtual water resource utilization efficiency of the tertiary industry exhibited an upward trend, with the average efficiency across all sectors increasing from 0.393 to 0.594—a cumulative growth of 51.15%, as shown in fig 5. This period can be divided into two stages:

2002–2010: High-Speed Growth Period, with a compound annual growth rate (CAGR) of 2.39%. The fastest growth occurred from 2002 to 2005, reaching an annualized rate of 3.44%.

2010–2020: Slowdown Period, with the CAGR decreasing to 1.95%. The growth further moderated to 1.65% from 2017 to 2020, refl

Figure 3 Line Chart of Virtual Water Resource Utilization Efficiency by Sector during 2002 - 2020

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As shown in Figure 3, the efficiency gradient exhibits distinct stratification, with a polarization between **high-efficiency sectors** (mean ≥ 0.7) and **low-efficiency sectors** (mean ≤ 0.35). High-efficiency sectors are concentrated in technology-intensive and policy-oriented fields (e.g., financial industry, environmental management), while low-efficiency sectors are mostly labor-intensive and traditional service industries (e.g., accommodation and catering, resident services).

High-efficiency sectors show stable growth:

Water Conservancy, Environment, and Public Facilities Management (efficiency value 0.934 in 2020) and the Financial Industry (0.874) consistently lead, with CAGRs of 0.45% and 0.88%, respectively. The former benefits from direct links to water resource management and rapid technological iteration, while the latter reduces physical resource dependence through digital trans-formation.

Mid-efficiency sectors demonstrate significant growth:

Information Transmission, Software, and In-formation Technology Services increased from 0.338 in 2002 to 0.580 in 2020—a substantial rise. As a knowledge-and-technology-intensive sector, continuous technological progress has optimized water use processes and promoted the adoption of water-saving technologies and equipment. Leasing and Business Services grew from 0.436 in 2002 to 0.659 in 2020, likely driven by improved industry standards, increased corporate focus on sustainable development, and implementation of water-saving measures.

Table 5 Table of Virtual Water Resource Utilization Efficiency by Sector during 2002–2020

Industry	Year								Mean
	2002	2005	2007	2010	2012	2015	2017	2020	
01	0.230	0.264	0.299	0.335	0.371	0.408	0.443	0.479	0.354
02	0.273	0.308	0.344	0.381	0.417	0.453	0.488	0.522	0.398
03	0.085	0.107	0.132	0.159	0.190	0.222	0.255	0.290	0.180
04	0.338	0.374	0.410	0.446	0.481	0.515	0.548	0.580	0.461
05	0.765	0.785	0.802	0.819	0.834	0.848	0.861	0.874	0.823
06	0.189	0.221	0.255	0.289	0.325	0.361	0.398	0.434	0.309
07	0.436	0.471	0.506	0.539	0.571	0.602	0.631	0.659	0.552
08	0.617	0.645	0.672	0.697	0.721	0.744	0.765	0.784	0.706
09	0.875	0.886	0.896	0.905	0.913	0.921	0.928	0.934	0.907
10	0.140	0.168	0.199	0.231	0.265	0.301	0.337	0.373	0.252
11	0.422	0.458	0.493	0.526	0.559	0.590	0.620	0.649	0.540
12	0.178	0.209	0.242	0.277	0.312	0.349	0.385	0.421	0.297
13	0.742	0.762	0.782	0.800	0.817	0.832	0.847	0.860	0.805
14	0.212	0.245	0.280	0.315	0.351	0.388	0.424	0.460	0.334
Mean	0.393	0.422	0.451	0.480	0.509	0.538	0.566	0.594	0.500

Low-efficiency sectors lag in improvement:

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Accommodation and Catering Services (multi-year mean 0.180) only achieved 30.3% of the overall mean in 2020, with the gap widening annually (from 0.308 in 2002 to 0.304 in 2020). Resident Services (multi-year mean 0.252) also show slow progress. These sectors suffer from fragmented operations, limited management capacity of small and micro enterprises, and low penetration of water-saving technologies.

Stochastic Frontier Analysis

The results of the stochastic frontier analysis are presented in Table 6. From the overall model validity test, the model passes the joint significance test (Wald chi2(5)), indicating that the selected variables have overall explanatory power. The proportion of technical inefficiency variance, gamma = 0.7544984, shows that 75.45% of the error originates from the technical inefficiency term, with only 24.55% attributed to random noise.

The analysis of variable coefficients indicates that the estimated coefficient of sectoral added value in the reciprocal of virtual water consumption model is 0.4611978 and passes the significance test. This positive correlation reflects the promoting effect of industrial structure upgrading or technological intensification on water resource utilization efficiency. The estimated coefficient of labor input is -0.4588328, significantly negative, indicating that an increase in labor input significantly raises the scale of water resource input. The capital input variable did not pass the significance test,showing its impact on water resource input is statistically insignificant. The estimated coefficient of technological R&D investment is 0.4795237 (at the 5% significance level), suggesting that increased R&D investment significantly reduces dependence on fresh water by promoting the innovation and application of water-saving technologies and improving the recycling efficiency of water resources. The estimated coefficient of pollution control investment is 0.3691577 (at the 1% significance level), reflecting that increased environmental governance investment encourages industries to strengthen water resource protection and rational use—through measures such as reducing wastewater discharge and improving water quality—thereby significantly decreasing water resource input. Additionally, the inefficiency decay rate (eta = 0.099) shows that technical inefficiency decreases at an annual rate of 9.9%, meaning the efficiency gap between industries narrows gradually over time. However, the pace of improvement remains slow, necessitating stronger policy intervention to accelerate efficiency enhancement.

Table 6 Stochastic Frontier Model Regression Results

Variable	Coefficient	Std. Error	z	P>|z|
_cons	9.14949	2.309758	3.96	0.000
Sectoral Added Value	0.4611978	0.1242231	3.71	0.000
Labor Input	-0.4588328	0.1128231	-4.07	0.000
Capital Input	-0.0382183	0.0714376	-0.53	0.593
Technological R&D Input	0.4795237	0.2298477	2.09	0.037
Pollution Control Input	0.3691577	0.1279462	2.89	0.004
/eta	0.0989736	0.0247375	4.00	0.000
gamma	0.7544984	0.1493111		
Log likelihood	-23.944448			
Wald chi2(5)	63.11			

Analysis of the Technical Inefficiency Surface

The technical inefficiency term of virtual water consumption is analyzed using a fixed-effects model, with results presented in Table 7. The model's within-group R^2 is 0.7638, indicating strong explanatory power of independent variables for intra-industry efficiency fluctuations. However, the overall R^2 is low (0.2242), primarily because the fixed-effects model strips out time-invariant individual heterogeneity (rho = 0.943). The significance and direction of core variables highlight that environmental protection investment, technological innovation, and industrial structure upgrading are key dynamic factors driving efficiency improvements. Below is a detailed analysis of how each variable influences the technical inefficiency term of water resources:

Water Resource Endowment ($\beta = -2.2268$, $p < 0.01$) confirms the promoting effect of resource abundance on water-saving technological innovation by reducing technical inefficiency. Abundant water resources provide a tolerance space for industrial technology trials, facilitating experimental improvements in water use efficiency.

Industrial Structure ($\beta = -7.9037$, $p < 0.01$) exhibits the most pronounced negative effect: a 1% increase in the tertiary industry's share reduces the technical inefficiency term by 7.90%. This verifies the structural contribution of low-water-consumption industries to efficiency enhancement, as a higher proportion of tertiary sectors aligns with more water-efficient production patterns.

Technological Development ($\beta = -3.2746$, $p < 0.01$) and **Education Level** ($\beta = -0.8513$, $p < 0.01$) show significant negative correlations, reflecting the roles of technological innovation in process improvement and human capital in management optimization, respectively. Technological progress drives the adoption of water-saving technologies, while educated labor enhances operational efficiency through better resource management.

Environmental Protection Investment ($\beta = -0.8149$, $p < 0.01$) demonstrates a direct marginal effect: increased investment in environmental governance improves water resource utilization efficiency by upgrading sewage treatment facilities and promoting water-saving technologies, thereby reducing waste and enhancing reuse.

Notably, the positive effects of **urbanization process ($\beta = 14.8615$, $p < 0.01$)** and **economic development level ($\beta = 3.2532$, $p < 0.01$)** reveal a dual-pressure mechanism. Urbanization intensifies water supply-demand imbalances through population concentration, while economic growth outpaces efficiency improvements, leading to increased inefficient water consumption. **Industry endowment ($\beta = 0.1680$, $p = 0.160$)** lacks statistical significance, likely due to the complex relationship between technical intensity and water use efficiency in the sampled industries or limitations in data observation dimensions, which may obscure clear associations.

Table 7 Technical Inefficiency Term Regression Results

Variable	Coefficient	Std. Error	t	P>|t|
Water Resource Endowment	-2.226846	0.6982126	-3.19	0.007
Industrial Structure	-7.903651	2.324279	-3.40	0.005
Industry Endowment	0.1679892	0.1126267	1.49	0.160
Urbanization Process	14.86153	4.516941	3.29	0.006
Economic Development	3.25316	0.9615347	3.38	0.005

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Scientific and Technological Development	-3.27464	0.9695216	-3.38	0.005
Education Development	-0.8513252	0.2509342	-3.39	0.005
Degree of Environmental Protection Investment	-0.8149081	0.2438856	-3.34	0.005
rho	0.94295681			
Overall R - squared	0.2242			
Within R - squared	0.7638			

Conclusion

This study employs an input-output model to measure the virtual water footprint of 14 sectors in China's tertiary industry from 2002 to 2020, and uses the Shephard water footprint distance function and a stochastic frontier model to conduct an in-depth exploration of virtual water resource utilization efficiency and its influencing factors. The following conclusions are drawn:

Sectoral Virtual Water Footprint Measurement

From 2002 to 2020, the total annual virtual water footprint of the tertiary industry exhibited fluctuating trends, primarily associated with macroeconomic conditions, industrial structure adjustments, and the implementation of water-saving measures. At the sectoral level, accommodation and catering services, education, and other sectors had relatively high multi-year average virtual water consumption, while the financial industry, health care, and social work sectors had lower values. Sectors such as scientific research and technical services showed relatively high average annual growth rates in virtual water consumption, whereas sectors like wholesale and retail trade experienced negative growth.

Virtual Water Resource Utilization Efficiency Measurement

Over 2002–2020, the overall virtual water resource utilization efficiency of the tertiary industry showed an upward trend, though the growth rate gradually slowed, reflecting diminishing marginal returns and a narrowing scope for technological improvements. A distinct efficiency gradient emerged: high-efficiency sectors, concentrated in technology-intensive and policy-oriented fields, demonstrated stable growth; mid-efficiency sectors showed significant efficiency improvements; low-efficiency sectors, mostly labor-intensive and traditional service industries, lagged in progress.

Stochastic Frontier Analysis

The model passed the joint significance test, confirming the overall explanatory power of the selected variables. Most of the error was attributed to the technical inefficiency term. Sectoral added value was positively correlated with virtual water consumption, promoting water resource utilization efficiency; increased labor input led to higher water resource input; capital input had no significant impact on water resource input; increased technological R&D and pollution control investments significantly reduced water resource input. Technical inefficiency decreased at an annual rate of 9.9%, but the pace of improvement remained slow.

Technical Inefficiency Surface Analysis

Results from the fixed-effects model indicated strong explanatory power of independent variables for intra-industry efficiency fluctuations. Improvements in water resource endowment, industrial structure, technological development, education level, and environmental protection investment significantly reduced the technical inefficiency term of water resources. Conversely, urbanization and economic development were associated with increased technical inefficiency, while industry endowment had no significant effect, likely due to complex correlations or data limitations.

Based on the research findings, the following recommendations are proposed to further improve virtual water resource utilization efficiency in the tertiary industry:

Optimize Industrial Structure for Low-Water-Consumption Transitions

Continue to adjust the industrial structure toward low-water-consumption and high-efficiency sectors by accelerating the transformation and upgrading of water-intensive traditional service industries. Encourage the development of technology-intensive and knowledge-intensive service sectors with low water consumption, thereby facilitating structural optimization and enhancing overall water resource utilization efficiency.

Increase Investment in Water-Saving Technology Innovation and Adoption

All sectors should prioritize research and development (R&D) investments to drive the innovation and application of water-saving technologies. Sectors with high average annual growth rates in virtual water consumption should particularly focus on developing and adopting advanced water-saving technologies and equipment to improve water recycling efficiency and reduce reliance on fresh water resources.

Strengthen Education and Environmental Awareness for Sustainable Practices

Enhance educational levels and environmental consciousness by strengthening specialized education in water resource management at universities, cultivating professionals with water-saving awareness and management capabilities. Through targeted education and advocacy, raise environmental awareness among the public and enterprises, prompting active adoption of water-saving measures to improve utilization efficiency.

Expand Environmental Protection Investment for Infrastructure and Technology Upgrades

Governments and enterprises should increase investments in environmental protection projects, including sewage treatment and water resource recycling, to modernize water treatment facilities and promote the adoption of water-saving technologies and equipment. Incentivize enterprises to implement environmentally friendly and efficient production processes, thereby reducing water waste and technical inefficiencies.

Balance Urbanization, Economic Growth, and Water Resource Management

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Address the challenges of urbanization and economic development by strengthening water resource management and supply system construction. Rationalize urban water planning, promote the use of water-saving appliances and infrastructure, and enhance urban water utilization efficiency. During economic growth, prioritize improvements in water resource efficiency to avoid excessive consumption and waste, ensuring coordinated development between economic progress and water resource protection.

These recommendations align with the study's empirical insights, aiming to provide actionable strategies for achieving sustainable water resource use in the tertiary industry through structural optimization, technological innovation, human capital development, and policy intervention.

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