International Journal of Electric Power and Energy Studies
ISSN: 3006-2004 (Print), ISSN: 3006-0826 (Online) | Volume 2, Number 3, Year 2024
DOI: https://doi.org/10.62051/ijepes.v2n3.14
Journal homepage: https://wepub.org/index.php/IJEPES/index

Measurement and Influencing Factors of Total Factor Water Resources Utilization Efficiency in the Yellow River Basin

Lihong Zhao*

School of Economics, Ocean University of China, Qingdao, China
*Corresponding Author

ABSTRACT

This paper focuses on the total factor water resources utilization efficiency (WRUE) as the research object, employing the Stochastic Frontier Analysis (SFA) model based on the transcendental logarithmic production function to measure the WRUE of nine provinces in the Yellow River Basin of China from 2012 to 2021, obtains WRUE values for each province. And then, we perform a regression analysis of influencing factors using the Tobit model. The results indicate that: (1) The average value of WRUE of nine provinces in the Yellow River Basin is 0.541, which deviates greatly from the fully effective frontier of SFA, with an overall downward trend during the study period. (2) There is a significant polarization of WRUE among the provinces. Inner Mongolia exhibits the highest WRUE at 0.978, close to the SFA efficient frontier, while Ningxia has the lowest WRUE at only 0.314; the remaining provinces display efficiency values between 0.4 and 0.6. (3) Among the influencing factors affecting the WRUE, the value added of the primary industry, per capita disposable income, and the number of reservoirs have a significant positive impact on the WRUE. In contrast, the value added of the secondary industry, local financial environmental protection expenditures, comprehensive water supply production capacity, and per capita daily water consumption negatively affect the WRUE.

KEYWORDS

Yellow River Basin; Water Resources Utilization Efficiency; SFA Model; Tobit Regression; Analysis of Influencing Factors.

1. INTRODUCTION

China faces the challenge of a relative shortage of water resources[1]. Although the total amount of water resources in the country is 2663.4 billion cubic meters, according to the statistics of the China Water Resources Bulletin, the total water consumption in 2022 reached as high as 599.7 billion cubic meters, and the per capita comprehensive water consumption is only 425 cubic meters[2]. Many regions are facing severe water resource utilization problems. As a major grain production base and important economic region, the Yellow River Basin has water resources as an important foundation for its economic development[3]. The water shortage problem not only imposes significant constraints on agriculture, industry and the tertiary sector, but also has a great restriction on regional ecological protection and high-quality development[4]. Data from the National Bureau of Statistics shows that the total water consumption in the Yellow River Basin is 123.61 billion cubic meters, of which agricultural water consumptiion is 77.93 billion cubic meters (accounting for 63.05%), industrial use is 13.22 billion cubic meters (10.69%), domestic use is 20.57 billion cubic meters (16.64%), and ecological use is 11.89 billion cubic meters (9.62%). This indicates that agriculture is the main water resource utilization sector in the Yellow River Basin, while industrial, domestic, and ecological water consumption are relatively low.

Regarding the current state of water resource utilization efficiency in the Yellow River Basin, agricultural irrigation models require significant water consumption[5], and China's irrigation infrastructure and modern techniques are relatively underdeveloped, leading to high water consumption but low utilization efficiency in agriculture. In industry, rapid development during China’s industrialization has resulted in sharp increases in water consumption, while many industrial enterprises in the Yellow River Basin waste water significantly[6–8]. Water-saving technologies and clean processes are not yet widely adopted, leading to high wastewater discharge and low water recycling rates[9]. In domestic and ecological water use, urbanization has increased household water consumption, prompting the government to strengthen urban water supply infrastructure and management to enhance stability and reliability[10,11]. Efforts have been made to raise public awareness about water conservation and promote rational water use, but there is still room for improvement in water utilization efficiency.

The report of the 20th CPC National Congress emphasized the importance of "promoting green development, fostering harmony between humanity and nature, and coordinating the governance of water resources, water environment, and water ecology." The serious shortage and pollution of water resources have become prominent ecological issues[12]. To address these challenges and advance the construction of a "Beautiful China," measures can be taken to control total water usage, enhance water resource management and pollution control, and improve WRUE[13]. Increasing WRUE is seen as a fundamental approach to resolving the contradiction between insufficient water resource capacity and economic development[14]. As a critical water resource replenishment area, improving WRUE in the Yellow River Basin is vital for China's economic growth and the well-being of its people. However, the basin faces longstanding supply-demand conflicts, water pollution, and ecosystem degradation, which severely hinder sustainable regional development[15]. Additionally, excessive water resource development and irrational usage lead to waste and loss, while declining water quality adversely affects agricultural irrigation and domestic water supply[16,17], presenting significant challenges in the basin.In this context, enhancing water utilization efficiency and optimizing water resource allocation and management have become crucial for resolving water resource issues in the Yellow River Basin.

This study focuses on the nine provinces within the Yellow River Basin, measuring regional water resource utilization efficiency and analyzing its influencing factors. The aim is to provide a scientific basis for watershed-level water resource management decisions and to support policy-making aimed at improving WRUE.

2. MEASUREMENT OF WRUE

2.1. Stochastic Frontier Model

In traditional terms, the production function represents the maximum output achievable given a set of input factors. It is based on known input and output variables, reflecting the optimal production function that indicates the most efficient production level under ideal conditions, referred to as the technical frontier or production frontier. This serves as the deterministic component in the SFA model, expressed in the following basic form:

$$Y_i = f(x_i, \beta) \tag{1}$$

where Y is the output, i is the cross-sectional unit, x represents the input factors, and β is the coefficient to be estimated.

In reality, production efficiency can be affected by various factors. The inability to reach the maximum output frontier arises primarily from two reasons: First, internal technical inefficiencies-where not all production can achieve optimal efficiency-are measured by a technical inefficiency term u, indicating the relative production efficiency level due to technological inefficiency, with $0 \leq u \leq 1$, and assumed to follow a truncated normal distribution. The second reason encompasses generally unavoidable stochastic factors, such as natural disasters or financial crises, which are included in the model as a stochastic disturbance term v, assumed to follow a normal distribution and independent of u.

$$Y_i = f(x_i, \beta) e^{v_i - u_i} \tag{2}$$

Here, u represents the technical inefficiency term, while v is the stochastic disturbance term. Together, they constitute a composite disturbance term that indicates the difference between actual output and maximum possible output. This model integrates both stochastic error terms and deterministic frontier functions, allowing the measurement of production function residuals to reflect the difference between actual output and maximum possible output, thereby assessing the portion of output growth unexplained by input factors (such as capital and labor). Consequently, technical efficiency (TE) can be expressed as the ratio of expected output to the expected value of the stochastic frontier:

$$TE_i = \frac{E[Y]}{E[f(x_i, \beta)]} \tag{3}$$

Substituting equation (2) into (3) yields:

$$TE_i = \frac{E[f(x_i, \beta) e^{v_i - u_i}]}{E[f(x_i, \beta) e^{v_i - u_i} \mid u_i] = 0} = e^{-u_i} \tag{4}$$

The parameter γ represents the proportion of the variance attributed to technical inefficiency within the composite disturbance term, expressed as follows:

$$\gamma = \frac{\sigma_u^2}{\sigma_u^2 + \sigma_v^2} \tag{5}$$

where $0 \leq \gamma \leq 1$. The estimated value of γ can also serve as a basis for evaluating the appropriateness of the SFA model setup. Since external stochastic factors are uncontrollable, the focus of the research is primarily on internal technical causes. A higher γ indicates a larger share of technical inefficiency, making the use of the stochastic frontier model more reasonable.

2.2. Form of the Production Function

The specific forms of frontier production functions include the Cobb-Douglas production function, translog production function, generalized elasticity of substitution production function, and boundary production function. The translog production function is a nonlinear production function capable of capturing the nonlinear relationships between production factors, providing a more flexible data fit. It can approximate the true production function through Taylor series expansion and is widely applicable, showing a degree of tolerance to parameter estimation errors, thus yielding relatively reliable results.

Therefore, this study selects the translog production function as the frontier production function, expressed in its basic form as:

$$\ln y_i = \beta_0 + \beta_1 \ln x + +\beta_{11} (\ln x)^2 + \mathrm{v_i} - \mathrm{u_i} \tag{6}$$

When the model includes three explanatory variables k_i, l_i, w_i, the translog production function is represented as:

$$\ln y_i = \beta_0 + \beta_k \ln k_i + \beta_l \ln l_i + \beta_w \ln w_i + \beta_{kk} (\ln k_i)^2 + \beta_{ll} (\ln l_i)^2 + \beta_{ww} (\ln w_i)^2 + \beta_{kl} (\ln k_i)(\ln l_i) + \beta_{kw} (\ln k_i)(\ln w_i) + \beta_{lw} (\ln l_i)(\ln w_i) + \mathrm{v_i} - \mathrm{u_i} \tag{7}$$

In this equation, y represents economic output, k denotes capital input, l signifies labor input, and w indicates water resource input. The β parameters are to be estimated.

2.3. Variable Selection

This study employs the SFA model to measure the total factor water resource utilization efficiency in nine provinces of the Yellow River Basin from 2012 to 2021. The selected input and output variables are as follows, and corresponding data processing is conducted to ensure the accuracy and reliability of the indicator data:

(1) Economic Output Variable y: The "Gross Regional Product" (GDP) of each province is used to reflect the level of economic development. To eliminate the effects of inflation, 2012 is set as the base year, and the GDP deflator index is applied to calculate real output.

(2) Capital Input Variable k: The "Capital Stock" is chosen, representing the total fixed asset investment in a region, which reflects the region's productivity level and the accumulation of production equipment. Based on the relationship between capital formation and depreciation, this study utilizes the perpetual inventory method for data processing, calculated as follows:

$$k_{it} = (1 - \delta_i) k_{i\,t-1} + I_{it} \tag{8}$$

where k is the capital stock for region i in year t, I represents new investment in year t, and δ is the depreciation rate.

(3) Labor Input Variable l : The "Total Number of Employees" is selected to reflect the scale of labor resources and employment levels in a region. The employment for the current year is calculated as the average of the total number of employees at the end of the previous year and the end of the current year to enhance data validity.

(4) Water Resource Input Variable w: The "Total Water Consumption" of each province is utilized to measure the utilization of water resources, serving as an input variable to examine its impact on efficiency.

2.4. Data Sources

The nine provinces through which the Yellow River flows are: Qinghai, Sichuan, Gansu, Ningxia, Inner Mongolia, Shaanxi, Shanxi, Henan, and Shandong. To obtain the data for the aforementioned variables, this study primarily collects necessary information from the National Bureau of Statistics, local statistical bureaus, the Ministry of Water Resources' "China Water Resources Bulletin," and the "China Statistical Yearbook." Specifically, GDP and total employment data are sourced from the National Bureau of Statistics, capital stock data from the "China Statistical Yearbook," and total water usage data from the "China Water Resources Bulletin."

2.5. Empirical Results and Analysis

Measurement Results of WRUE in the Yellow River Basin,

Based on the data obtained, the SFA model was computed using Stata 17, resulting in the parameter estimates shown in Table 1.

The p-values for labor input and water resource input are both 0.000, indicating that these two input factors have a significant direct impact on output. The positive interaction coefficient of 0.66 between capital and labor suggests a complementary relationship, meaning that an increase in capital investment further promotes labor input. Conversely, the interaction coefficient between capital and water resource input is -0.62, indicating a substitution relationship. The γ value of 0.85 demonstrates a significant proportion of technical inefficiency, justifying the use of the stochastic frontier model. A positive η (>0) indicates an improvement in water resource utilization efficiency.

Table 1. Parameter Estimation Results

lng	Coefficient	Std. err.	z	P>|z|	[95% conf.	interval]
lnk	.7812556	.8818794	0.89	0.376	-.9471962	2.509707
lnl	-8.506433	1.628819	-5.22	0.000	-11.69886	-5.314006
lnw	6.944449	1.419625	4.89	0.000	4.162035	9.726863
lnk2	-.1826808	.1105872	-1.65	0.099	-.3994278	.0340662
lnl2	.5346009	.1970763	2.71	0.007	.1483384	.9208634
lnw2	.7076315	.3011588	2.35	0.019	.1173712	1.297892
lnk_lnl	.6631604	.2185736	3.03	0.002	.2347639	1.091557
lnk_lnw	-.6237506	.207052	-3.01	0.003	-1.029565	-.2179362
lnl_lnw	-1.01236	.4700767	-2.15	0.031	-1.933694	-.0910272
_cons	19.87078	4.881525	4.07	0.000	10.30317	29.4384
/mu	.4014209	.109723	3.66	0.000	.1863678	.616474
/eta	.1027268	.0135322	7.59	0.000	.0762042	.1292495
/lnsigma2	-3.027439	.6338155	-4.78	0.000	-4.269694	-1.785183
/lgtgamma	1.740064	.7859692	2.21	0.027	.1995924	3.280535
sigma2	.0484396	.0307017			.0139861	.1677663
gamma	.8506952	.0998282			.5497331	.963755
sigma_u2	.0412073	.0308339			-.0192261	.1016407
sigma_v2	.0072323	.0011659			.0049471	.0095175

The measurement results of WRUE for the nine provinces of the Yellow River Basin from 2012 to 2021 are presented in Table 2.

Overall, the mean total factor water resource utilization efficiency across the nine provinces of the Yellow River Basin is 0.541, showing a substantial deviation from the SFA's fully efficient frontier. There is a declining trend from 2012 to 2021, with an overall decrease of 0.2. Regionally, significant polarization is observed in water resource utilization efficiency among the provinces. Inner Mongolia exhibits the highest efficiency, with an average of 0.978, closely approaching the SFA efficient frontier. Shaanxi follows with an average efficiency of 0.664, while Ningxia has the lowest efficiency at only 0.314, showing a considerable deviation from the optimal frontier. The remaining provinces in the Yellow River Basin have efficiencies ranging from 0.4 to 0.6.

Table 2. WRUE in the Yellow River Basin (2012-2021)

Province	2021	2020	2019	2018	2017	2016	2015	2014	2013	2012	Average
Inner Mongolia	0.967	0.970	0.973	0.976	0.978	0.980	0.982	0.984	0.985	0.987	0.978
Shaanxi	0.530	0.564	0.597	0.627	0.657	0.684	0.710	0.734	0.756	0.777	0.664
Shandong	0.432	0.469	0.505	0.540	0.573	0.605	0.636	0.664	0.691	0.717	0.583
Sichuan	0.360	0.398	0.435	0.472	0.508	0.543	0.576	0.608	0.638	0.667	0.521
Shanxi	0.318	0.356	0.393	0.431	0.468	0.504	0.539	0.572	0.604	0.635	0.482
Gansu	0.284	0.322	0.359	0.397	0.434	0.471	0.507	0.542	0.575	0.607	0.450
Qinghai	0.279	0.316	0.354	0.391	0.429	0.466	0.502	0.537	0.570	0.603	0.445
Henan	0.271	0.307	0.345	0.383	0.420	0.457	0.494	0.529	0.563	0.595	0.436
Ningxia	0.157	0.188	0.221	0.256	0.293	0.330	0.368	0.405	0.443	0.479	0.314
Average	0.400	0.432	0.465	0.497	0.529	0.560	0.590	0.619	0.647	0.674	0.541

2.5.1. Economic Explanation for Regional Differences in WRUE

The total factor water resource utilization efficiency has shown a downward trend from 2012 to 2021. This decline can be attributed to the rapid economic development during this period, where the pursuit of economic returns often overshadowed the need for controlled water resource input and a lack of water conservation awareness, leading to overall low WRUE levels.

Significant regional disparities in WRUE exist among the nine provinces in the Yellow River Basin. Inner Mongolia ranks highest in WRUE, thanks to its strict water resource management policies and the implementation of responsibility systems for total water usage and intensity control, which have effectively reduced wasteful practices and improved WRUE. Data indicates that while water resource input in Inner Mongolia has been decreasing year by year, economic output has been increasing, reflecting its high efficiency in water utilization.

Ningxia, located in the arid northwest, suffers from scarce and unevenly distributed surface water resources, compounded by weak water infrastructure and overall low technological levels, resulting in the lowest WRUE. Comparatively, Shaanxi, Shandong, and Sichuan are more economically developed within the Yellow River Basin and have advanced water management technologies, resulting in relatively high WRUE.

In contrast, Shanxi, Gansu, Qinghai, and Henan exhibit lower efficiencies, which can be explained by significant industrial water pollution challenges leading to deteriorating water quality. Additionally, poor management of industrial and urban water use, inadequate wastewater treatment, and challenges posed by climate change and drought contribute to insufficient water supply, further impacting WRUE. To further investigate the specific causes, the following section analyzes the factors influencing water resource utilization efficiency.

3. ANALYSIS OF INFLUENCING FACTORS OF WRUE

3.1. Selection of Indicators and Data Sources

The regional differences in WRUE are influenced not only by input and output indicators, but also by various external factors, including technological advancements, policies and institutional frameworks, and socio-economic factors. The introduction of advanced water-saving technologies and improvements in irrigation infrastructure play a crucial role in enhancing WRUE. Effective water resource management policies, pricing mechanisms, and usage regulations can incentivize water conservation behaviors and optimize water resource allocation, thereby improving WRUE. Regions with higher population density, elevated economic development levels, and more optimized industrial structures typically demonstrate higher WRUE.

Considering the impacts of technology, institutional frameworks, and socio-economic conditions, as well as the availability and accuracy of data, this study primarily focuses on the following variables:

(1) Industrial Structure: To avoid multicollinearity, this study utilizes "value added of the primary industry" and "value added of the secondary industry" to measure regional differences in industrial structure. The primary industry mainly encompasses agriculture, while the secondary industry mainly covers manufacturing; together, they account for 73.74% of total water consumption in the Yellow River Basin. The industrial structure affects regional water usage, which in turn influences WRUE.

(2) Local Government Environmental Protection Expenditure: Higher government spending on environmental protection reflects a greater emphasis on sustainable ecological development. This promotes the formulation of scientific and rational water management policies and guides the effective allocation and utilization of water resources.

(3) Per Capita Disposable Income: This indicator reflects individual income levels. As per capita disposable income rises, residents become more conscious of quality of life and environmental protection, fostering a conservation mindset regarding water resources and leading to more efficient usage.

(4) Comprehensive Water Supply Production Capacity: This is calculated based on the design capacity of water supply facilities, encompassing extraction, purification, and distribution. Areas with abundant and easily accessible water resources often experience greater waste, resulting in lower WRUE. Conversely, regions where water is scarce tend to have higher WRUE.

(5) Per Capita Daily Water Consumption: This measures the average daily water usage per person. A high per capita daily consumption typically indicates excessive water use, which can lower WRUE. Additionally, in economically underdeveloped regions, the lack of advanced water-saving technologies often leads to higher consumption levels to meet basic needs, further diminishing WRUE.

(6) Number of Reservoirs: As a critical infrastructure component, reservoirs facilitate the regulation and storage of water resources. By adjusting reservoir storage and discharge, they can provide stable water supplies during droughts while storing excess water in wet seasons, thereby enhancing WRUE and promoting rational allocation.

The data for these indicators can be obtained from the National Bureau of Statistics, the "China Water Resources Bulletin," and the "China Statistical Yearbook." Specifically, data on "value added of the primary and secondary industries" and "per capita disposable income" come from the National Bureau of Statistics, while "local government environmental protection expenditure" is sourced from the "China Statistical Yearbook." Data on "comprehensive water supply production capacity," "per capita daily water consumption," and "number of reservoirs" are obtained from the "China Water Resources Bulletin."

3.2. Tobit Model and Variable Explanation

Given that the total factor water resource utilization efficiency calculated using the SFA model ranges between 0 and 1 and the distribution of the composite random error term is asymmetric, using Ordinary Least Squares (OLS) would not yield reliable estimates of the technical inefficiency term u. Since u follows a non-negative truncated normal distribution, this study employs the Tobit model for regression analysis.

The Tobit regression is designed for datasets with censored values, separating the observed portion (which follows a truncated normal distribution) from the unobserved portion (which follows a normal distribution). The aim is to quantitatively assess the main factors influencing the WRUE in the Yellow River Basin. The model is expressed as:

$$\mathrm{TEW} = \beta_0 + \sum_{i=1}^{k} \beta_k X_k + u_i \quad (9)$$

where TEW represents total factor water resource utilization efficiency, and i=1,2,…,k denotes each influencing factor. The random error term u is assumed to follow a normal distribution.

In this model, water resource utilization efficiency is the dependent variable, while the selected influencing factors-such as "value added of the primary industry," "value added of the secondary industry," "local government environmental protection expenditure," "per capita disposable income," "comprehensive water supply production capacity," "per capita daily water consumption," and "number of reservoirs"-serve as independent variables X_k,k=1,2,…,7. The Tobit regression model will thus estimate the contribution of each factor to WRUE.

4. EMPIRICAL RESULTS AND ANALYSIS

Using Stata 17 for regression analysis of the Tobit model, the parameter estimation results are summarized in Table 3.

Table 3. Tobit Regression Results

technical inefficiency	Coefficient	Std.err.	t	P>|t|	[95% conf. interval]	
value added of the primary industry	0.1859358	0.0426027	4.36	0	0.1012008	0.2706708
value added of the secondary industry	-0.1226259	0.0444083	-2.76	0.007	-0.2109523	-0.0342995
local government environmental protection expenditure	-0.1303148	0.0482005	-2.7	0.008	-0.2261836	-0.0344459
per capita disposable income	0.5789979	0.0469965	12.32	0	0.4855238	0.6724721
comprehensive water supply production capacity	-0.2006665	0.0579526	-3.46	0.001	-0.3159319	-0.0854011
per capita daily water consumption	-0.412948	0.0826139	-5	0	-0.5772637	-0.2486323
the number of reservoirs	0.0992052	0.0369188	2.69	0.009	0.0257751	0.1726352
_cons	-2.223937	0.6126973	-3.63	0	-3.442567	-1.005307
var	0.0109882	0.001638			0.0081688	0.0147806

The regression results indicate that the value added of the primary industry, per capita disposable income, and the number of reservoirs have a significant positive impact on water resource utilization efficiency, while the value added of the secondary industry, local government environmental protection expenditure, comprehensive water supply production capacity, and per capita daily water consumption negatively affect efficiency.

Economic Interpretation of Regression Results:

(1) Value Added of the Primary Industry: The estimated coefficient is positive and significant, indicating that the rational use of agricultural water in the industrial structure affects water resource utilization efficiency. An estimated coefficient of 0.19 suggests that a one-unit increase in primary industry value added leads to a 0.19 unit increase in total factor water resource utilization efficiency. As agriculture is the main water-consuming sector in the Yellow River Basin, promoting water-saving irrigation methods is beneficial for improving efficiency. Reducing the proportion of high-water-consuming industries is a key approach for building energy-efficient industries.

(2) Value Added of the Secondary Industry: The estimated coefficient is negative but not significant. This may be due to the high pollution levels associated with industrial activities, which often involve pollutant discharge and wastewater generation. Without appropriate environmental protection measures, this leads to water resource depletion and lowers efficiency. The lack of significance could stem from a small sample size, poor data quality, or an incomplete model specification, suggesting a

need to expand the sample size, improve measurement methods, or introduce additional relevant control variables for a more comprehensive analysis.

(3) Local Government Environmental Protection Expenditure: The estimated coefficient is negative and also not significant. While increased government funding for environmental protection should incentivize enterprises to conserve water and reduce emissions, the lack of targeted investment—such as in green technology development and wastewater treatment—may have resulted in insufficient environmental protection outcomes.

(4) Per Capita Disposable Income: The estimated coefficient is positive and significant, with a value of 0.57. This indicates that a one-unit increase in per capita disposable income results in a 0.57 unit increase in total factor water resource utilization efficiency. Economic growth and rising incomes enhance people's awareness of the rational use and conservation of water resources. Higher income levels encourage residents to invest in water-saving devices, adopt conservation measures, and support water management and protection initiatives, thus improving overall WRUE.

(5) Comprehensive Water Supply Production Capacity: The estimated coefficient is negative and significant, with a value of -0.2. This implies that an increase in comprehensive water supply capacity leads to a 0.2 unit decrease in total factor water resource utilization efficiency. The negative relationship indicates that expanding supply capacity does not correlate with increased WRUE, potentially leading to excessive consumption and waste due to insufficient management practices.

(6) Per Capita Daily Water Consumption: The estimated coefficient is also negative and significant, suggesting that higher daily water consumption contributes to overuse and waste of water resources, further reducing WRUE.

(7) Number of Reservoirs: The estimated coefficient is positive but not significant. This suggests that other influential factors may have a more substantial impact on water resource utilization efficiency, overshadowing the effect of reservoir numbers. However, reservoirs play a crucial role in managing and utilizing water resources by providing stable supplies and adjusting for seasonal variations. Therefore, they have the potential to enhance WRUE through better water resource management.

5. RESEARCH CONCLUSIONS AND POLICY RECOMMENDATIONS

5.1. Research Conclusion

Based on the empirical results from the SFA and Tobit models, the following conclusions can be drawn regarding the total factor water resource utilization efficiency in the Yellow River Basin from 2012 to 2021:

(1) The average total factor water resource utilization efficiency across the nine provinces in the Yellow River Basin is 0.541, indicating significant deviation from the SFA efficient frontier. This suggests that there is considerable room for improvement in current water resource utilization practices. Enhancements in technology and management methods can further increase efficiency, revealing systemic issues such as inadequate water resource management and poor policy implementation. Strengthening water resource management is crucial for achieving higher efficiency levels and promoting sustainable development in the Yellow River Basin.

(2) There is a general downward trend in water resource utilization efficiency in the Yellow River Basin during the study period, reflecting inefficiencies in resource allocation. This decline can be attributed to factors such as poor water resource management, water pollution, outdated technology, and over-extraction of water resources. Increased awareness and action from both the government and the public are needed to address these issues for sustainable and efficient water use.

(3) There is significant polarization in WRUE among the provinces. Inner Mongolia has the highest efficiency at 0.978, closely approaching the SFA frontier, followed by Shaanxi at 0.664. In contrast,

Ningxia has the lowest efficiency at only 0.314, indicating substantial deviation from optimal performance. Other provinces fall within the range of 0.4 to 0.6. These differences highlight varying water resource management practices, economic structures, and social developments, necessitating targeted improvements in lagging provinces.

(4) Among the driving factors, the value added from the primary industry, per capita disposable income, and the number of reservoirs positively influence water resource utilization efficiency. Conversely, the value added from the secondary industry, local government environmental protection expenditure, comprehensive water supply production capacity, and per capita daily water consumption have negative impacts. This indicates that growth in agriculture, rising resident incomes, and reservoir construction contribute positively to efficiency, while industrial development, insufficient environmental expenditure, overcapacity in water supply, and increased daily consumption negatively affect it.

5.2. Policy Recommendations

Based on the above conclusions, the following policy recommendations aim to enhance water resource utilization efficiency in the Yellow River Basin:

(1) To improve overall WRUE and narrow the gap between average values and the frontier, the government should formulate comprehensive policies for basin-level water resource management. This includes establishing unified management systems across provinces, understanding socio-economic relationships and water resource characteristics, designing incentive mechanisms, and ensuring efficient allocation and utilization of water resources. A robust monitoring network should be established to collect data on water resource status, allowing for regular assessments of quality and efficiency levels, and implementing incentives or penalties based on performance.

(2) Given the observed decline in WRUE, the government should reform water resource management systems and increase funding for research and innovation. This will support the adoption of advanced water utilization technologies and facilities. Public awareness campaigns should focus on the importance of water conservation, encouraging both enterprises and residents to adopt water-saving practices. Furthermore, laws and regulations promoting sustainable water management should be established, ensuring coordinated economic and environmental development.

(3) To mitigate the significant differences in WRUE, policies should encourage high-efficiency provinces to assist those with lower efficiency levels. Efficient water allocation should focus on areas with the highest returns. For regions like Ningxia, government oversight and strategic water resource reserves can enhance efficiency. In water-scarce areas like Henan, establishing water trading markets or quotas can promote fair competition and support efficiency improvements. Local governments should analyze the factors contributing to low efficiency and adopt successful management practices from more efficient provinces.

(4) Given the positive impacts of agricultural value added, per capita income, and reservoir construction, the government should promote improvements in irrigation infrastructure, encourage efficient agricultural practices, and provide subsidies for water-saving technologies. Additionally, strengthening the social security system and enhancing reservoir management capabilities are vital. To counter negative influences, the government should increase environmental regulation and investment, promote green manufacturing, and optimize water supply system designs to ensure effective water provision. Implementing pricing incentives for water use can also encourage residents to use resources wisely.

REFERENCES

[1] A. Omer, N.A. Elagib, M. Zhuguo, F. Saleem, A. Mohammed, Water scarcity in the Yellow River Basin under future climate change and human activities, Science of The Total Environment 749 (2020) 141446. https://doi.org/10.1016/j.scitotenv.2020.141446.

[2] J. Wei, Y. Lei, L. Liu, H. Yao, Water scarcity risk through trade of the Yellow River Basin in China, Ecological Indicators 154 (2023) 110893. https://doi.org/10.1016/j.ecolind.2023.110893.

[3] K. Zheng, T. Shao, J. Ning, D. Zhuang, X. Liang, X. Ding, Water quality, basin characteristics, and discharge greatly affect CDOM in highly turbid rivers in the Yellow River Basin, China, Journal of Cleaner Production 404 (2023) 136995. https://doi.org/10.1016/j.jclepro.2023.136995.

[4] X. Xiang, Q. Li, S. Khan, O.I. Khalaf, Urban water resource management for sustainable environment planning using artificial intelligence techniques, Environmental Impact Assessment Review 86 (2021) 106515. https://doi.org/10.1016/j.eiar.2020.106515.

[5] S. Kalogiannidis, D. Kalfas, G. Giannarakis, M. Paschalidou, Integration of Water Resources Management Strategies in Land Use Planning towards Environmental Conservation, Sustainability 15 (2023) 15242. https://doi.org/10.3390/su152115242.

[6] M. Hu, C. La, Y. Juhong, Green Water Resource Utilization Efficiency in Urban Agglomerations: Measurement, Spatiotemporal Variations and Influencing Factors, Journal of Resources and Ecology 14 (2023). https://doi.org/10.5814/j.issn.1674-764x.2023.06.007.

[7] W. Wu, Y. Zhu, W. Zeng, M. Wang, D. Yang, W. Chen, Green efficiency of water resources in Northwest China: Spatial-temporal heterogeneity and convergence trends, Journal of Cleaner Production 320 (2021) 128651. https://doi.org/10.1016/j.jclepro.2021.128651.

[8] J. Jiang, B.-C. Xie, Environmental efficiency evaluation of China's power system considering factor's spatial dependence: A dynamic spatial network DEA approach, Environmental Impact Assessment Review 104 (2024) 107329. https://doi.org/10.1016/j.eiar.2023.107329.

[9] H. Ma, Y. Ding, L. Wang, Measurement and Convergence Analysis of Green Water Utilization Efficiency, Journal of Natural Resources 32 (2017) 406–417. https://doi.org/10.11849/zrzyxb.20160381.

[10] J. Sohn, Watering cities: spatial analysis of urban water use in the Southeastern United States, Journal of Environmental Planning and Management 54 (2011) 1351–1371. https://doi.org/10.1080/09640568.2011.575188.

[11] J. Hu, S. Wang, F. Yeh, Total-factor water efficiency of regions in China, Resources Policy 31 (2006) 217–230. https://doi.org/10.1016/j.resourpol.2007.02.001.

[12] B.K. Edziah, E.E.O. Opoku, Enhancing energy efficiency in Asia-Pacific: Comprehensive energy policy analysis, Energy Economics 138 (2024) 107831. https://doi.org/10.1016/j.eneco.2024.107831.

[13] X. Wang, B. Cui, Y. Chen, T. Feng, Z. Li, G. Fang, Dynamic changes in water resources and comprehensive assessment of water resource utilization efficiency in the Aral Sea basin, Central Asia, Journal of Environmental Management 353 (2024) 120198. https://doi.org/10.1016/j.jenvman.2024.120198.

[14] J. Wei, Y. Wei, A. Western, Evolution of the societal value of water resources for economic development versus environmental sustainability in Australia from 1843 to 2011, Global Environmental Change 42 (2017) 82–92. https://doi.org/10.1016/j.gloenvcha.2016.12.005.

[15] Y. Zhao, Y. Wang, Y. Wang, Comprehensive evaluation and influencing factors of urban agglomeration water resources carrying capacity, Journal of Cleaner Production 288 (2021) 125097. https://doi.org/10.1016/ j.jclepro.2020.125097.

[16] Z. Li, K. Yu, J. Zhong, J. Yang, D. Zhang, J. Zhu, Spatial correlation network characteristics and influencing factors of water environmental efficiency in three major urban agglomerations in the Yangtze River Basin, China, Sustainable Cities and Society 104 (2024) 105311. https://doi.org/10.1016/j.scs.2024.105311.

[17] Y. Chen, B. Fu, Y. Zhao, K. Wang, M.M. Zhao, J. Ma, J.-H. Wu, C. Xu, W. Liu, H. Wang, Sustainable development in the Yellow River Basin: Issues and strategies, Journal of Cleaner Production 263 (2020) 121223. https://doi.org/10.1016/j.jclepro.2020.121223.