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A Comparative Study of the Driving Factors of Water Resources Use Efficiency in China's Agricultural and Industrial Sectors

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Abstract: The efficient use of water resources has become an important topic in China. Research on measurement and driving factors is the foundation for improving water resources use efficiency (WRUE). In this paper, the super-efficiency slacks-based measure (SE-SBM) model is used to measure the WRUE of China from 2005 to 2021. The agricultural carbon emissions and chemical oxygen demand (COD) in industrial wastes are taken as undesirable by-products. The driving factors of WRUE are discussed with use of the Tobit regression model. The results show that China's agricultural WRUE ranges from 1.185 in Jilin to 0.687 in Ningxia. In the industrial sector, the WRUE ranges from 1.399 in Beijing to Jiangxi 0.212. The economic structure and development level, water resources endowment, government influence and environmental regulation, agricultural planting scale and urbanization rate have impacts on WRUE. Precautionary measures need to be applied to prevent inefficient WRUE caused by the declining share of the industrial sector in the economic structure. More financial support should be focused on water-saving irrigation in agriculture and energy and resource efficiency in industry. The organizational structure and technological advantages of urbanization should also be emphasized in efforts to improve water efficiency.

Keywords: water resources use efficiency; driving factors; SE-SBM; agricultural water; industrial water

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1. Introduction

Water resources are important natural and strategic economic resources that underpin the survival and development of human societies [1,2]. Under the challenge of climate change, water scarcity has become a growing problem [3,4]. By 2025, approximately two-thirds of the population will have to live under water-stressed conditions. Water resources use efficiency (WRUE) is a crucial indicator of the sustainability of an economy [5,6]. Therefore, comprehensively improving WRUE is an urgent priority to address the prominent imbalance between water supply and demand [7]. Governments are encouraging efficiency measures to conserve water resources [8]. So, the sustainable development of water resources and green and high-quality economic development are promoted [9].

The total water resources of China in 2022 were 2708.81 billion m^3, ranking fourth in the world [10]. However, the per capita water resources possession is only one quarter of the world level, making China one of the 13 countries with the poorest water resources in the world [7,11]. China is currently in a critical stage of industrialization and modernization. However, the rough economic development of the past decades has led to low WRUE in China. Water scarcity is particularly pronounced [12,13]. Research on the measurement and driving factors of WRUE is the foundation for improving [14], which would provide the support for alleviating water scarcity.

There are various methods to measure WRUE. The parametric approach represented by stochastic frontier analysis (SFA) [15,16] and the non-parametric approach typified by data envelopment analysis (DEA) are the dominant methods. There is a complex interaction between the environment and the production process during the use and treatment of water resources. It is difficult to apply an explicit functional form to evaluate the WRUE by parametric methods. Therefore, non-parametric methods were introduced to measure WRUE. The super-efficiency DEA model [17], three-stage DEA model [18], slacks-based measure (SBM) model [19], undesirable output super efficiency slacks-based measure (SE-SBM) model [20], network DEA model [21], and other various DEA improvement methods have been developed. In the spatial dimension, WRUE has been measured at the urban [22], provincial [23,24], basin [19,25], and national [21,26] levels. Scholars have evaluated WRUE in different water use sectors of agriculture, industry, the domestic sphere, and ecology. Huang et al. [27] evaluated the efficiency of the plantation, forestry, animal husbandry, and fishery industries, concluding that China's overall agricultural WRUE has shown a fluctuating downward trend. Shi et al. [28] and Qi and Song [29] evaluated the WRUE of the Yangtze River Economic Belt for agriculture and industry, respectively.

The literature has also explored the drivers of WRUE changes from natural, economic, and social perspectives. Yu and Liu [30] concluded that WRUE is negatively correlated with investment in wastewater treatment projects and industrial water use structure, and positively correlated with the total amount of water supplied and the level of science and technology. Ma et al. [31] concluded that the technological progress has a positive impact on WRUE, whereas water costs and environmental pollution reduced the efficiency. For the factors affecting agricultural WRUE, researchers have focused on resource endowment [32], industrial structure [33], soil type [34], water conservancy facilities [35], and the agricultural planting structure [36]. The driving factors of industrial WRUE have been studied. Cheng and Zhang [37] argued that the water price is an important factor influencing industrial WRUE. He et al. [38] explored the impact of variables such as per capita gross domestic product (GDP), per capita water consumption, the proportion of secondary and tertiary industry water use, foreign direct investment, and research & development (R&D) intensity. Furthermore, scholars have also looked at the influence of environmental regulation [39], population density [22], and government policy [29].

These studies have provided evidence on the measurement and driving factors of WRUE. However, there are still some gaps in the research. On the one hand, the measurements of WRUE have focused on desirable outputs. The attention paid to undesirable outputs such as pollution emissions from industrial and agricultural production has been limited. As environmental issues are gradually being paid attention to, adding appropriate environmental indicators as undesirable outputs will undoubtedly make the measurement results reasonable. On the other hand, most studies have analyzed WRUE in society as a whole, or have focused on only one of the industrial or agricultural sectors in isolation. This makes comparative analysis between the agricultural and industrial sectors difficult. Neglecting undesirable outputs makes the study results invalid for supporting cleaner production and sustainability. The lack of comparative analysis will also make policy implications incompatible with both the agricultural and industrial sectors.

Therefore, this paper adopts the SE-SBM model with the undesirable outputs to measure WRUE in agriculture and industry in 31 provinces or cities in China. Then, Tobit regression is applied to investigate the driving factors in different water use sectors. For the first time, a comparative discussion is conducted on the driving factors of agricultural and industrial WRUE. The foundation for water management policy development from a comprehensive agriculture–industry perspective is provided.

The rest of the paper is organized as follows. Section 2 introduces the research methods and materials. Section 3 presents the results. Section 4 discusses the empirical results. Finally, Section 5 summarizes the main conclusions and proposes policy implications.

2. Methods and Materials

2.1. Research Methods

2.1.1. SE-SBM Model

The SBM model was originally proposed by Tone [40]. It is a non-radial and non-angular data envelopment analysis method. However, when multiple decision-making units (DMUs) are evaluated as effective in the SBM, the efficiency level of effective DMUs cannot be further distinguished. Andersen and Petersen proposed the super-efficiency model to resolve this [41]. Besides the outputs defined as "good" such as GDP, there are also "bad" or "undesirable" outputs such as wastewater, exhaust, and solid waste. Based on this, Tone [42] further proposed the SE-SBM model of undesirable outputs, which could comprehensively consider the relationship between inputs, outputs, and pollution. Therefore, an undesirable output-oriented SE-SBM model was selected to measure the WRUE.

The undesirable output SE-SBM model of water resources uses efficiency as follows [42]: In Equation (1), the objective function W is the efficiency value of the decision unit, i.e., the WRUE of each region in this paper; x_{ij} is the input i of the DMU j; y_{rj} is the output r of the DMUs j; s_i^-, s_r^{g+}, s_t^{b-} are the slack variables of the inputs, desirable outputs, and undesirable outputs, respectively; λ is the vector of weights. For a decision-making unit, it is valid if and only if its value is 1, i.e., it satisfies the equality of s^-, s^g, and s^b. Otherwise, the decision-making unit is invalid or has efficiency losses.

$$MinW = \frac{1 + \frac{1}{m}\sum_{i=1}^{m}\frac{s_i^-}{x_{ik}}}{1 - \frac{1}{q_1+q_2}\left(\sum_{r=1}^{q_1}\frac{s_r^{g+}}{y_{rk}^g} + \sum_{t=1}^{q_2}\frac{s_t^{b-}}{y_{tk}^b}\right)} \tag{1}$$

$$s.t.\begin{cases} \sum_{j=1,j\neq k}^{n} x_{ij}\lambda_j - s_i^- \leq x_{ik} \\ \sum_{j=1,j\neq k}^{n} y_{rj}^g\lambda_j + s_r^{g+} \geq y_{rk}^g \\ \sum_{j=1,j\neq k}^{n} y_{tj}^b\lambda_j - s_t^{b-} \leq y_{tk}^b \\ 1 - \frac{1}{q_1+q_2}\left(\sum_{r=1}^{q_1}\frac{s_r^{g+}}{y_{rk}^g} + \sum_{t=1}^{q_2}\frac{s_t^{b-}}{y_{tk}^b}\right) > 0 \\ s^- > 0, s^g > 0, s^b > 0, \lambda > 0 \\ i = 1,2,\cdots,m; r = 1,2,\cdots,q; j = 1,2,\cdots,n(j \neq k) \end{cases}$$

2.1.2. Tobit Regression Model

The Tobit model is a standard censored model. Tobit differs from discrete variable models or continuous variable models in that the dependent variable is restricted and consists of two types of equations. The efficiency obtained by the DEA model is affected by the input and output indicators and other environmental factors such as the regional economic level, labour market, and financial support [43]. The estimation of linear regression in the presence of censoring includes additional computational complications. The ordinary least squares regression produces inconsistent parameter estimates because the censored samples are not representative of the total. The values of the SE-SBM model measured in this paper are truncated data greater than 0. Therefore, the Tobit model is appropriate for exploring the drivers of WRUE.

The general form of the Tobit model is Equation (2) [44]. The negative values of the explanatory variable y_i are replaced by 0. The bias brought by the regression reduced.

$$y_i = \beta x_i + u_i \tag{2}$$

The model (2) can be transformed to:

$$WRUE_{it} = c + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_i X_i + \cdots + \beta_9 X_9 + \varepsilon_{it}(i = 1,2,\cdots,9) \tag{3}$$

where $WRUE_{it}$ is the WRUE considering undesirable outputs, i, t denote the values for different regions in different time periods, $X_i(i = 1, 2, \cdots, 9)$ are independent variables, which will be explained in detail below; $\beta_i(i = 1, 2, \cdots, 9)$ denote the coefficients to be estimated for the variables of interest; ε is the random error.

2.2. Variable Selection and Data

2.2.1. WRUE Measurement Variables

Measurement variables should be able to effectively reflect the economic, social and environmental impacts of water use. Regarding the input–output relationship of water resources use in the process of economic growth, Jorgenson and Stiroh [45] proposed the KLEM (capital, labor, energy, and materials) model. The KLEM model decomposes inputs into capital, labor, energy, and intermediate inputs, and outputs refer to desirable outputs of economic significance. While obtaining agricultural and industrial products, some undesirable by-outputs cannot be avoided. Referring to literature, the input–output index system is constructed.

(1) Agricultural sector

In agricultural production, inputs such as land, labor, and capital are indispensable. However, the carbon emissions that come with receiving crops are undesirable but objective. The rural population, amount of agricultural fertilizer (in tons), total power of agricultural machinery (in kilowatts), agricultural water consumption (m^3), and the effective irrigated area (hectares) are selected as the input indicators. The real GDP of agricultural output (in CNY) and the grain yield (tons) are the desirable output indicators. The undesirable output is agricultural carbon emissions (tons) [20,31,46] (Table 1).

Table 1. Input–output index system in agricultural WRUE.

Indicator	Name	Index	Units
Input indicators	Labor	Rural population	10,000 people
	Capital	Amount of agricultural fertilizers	10,000 tons
	Technology	Agricultural machinery power	10,000 kilowatts
	Natural resources	Agricultural water consumption	100 million m^3
		Effective irrigated area	1000 hectares
Output indicators	Desirable output	Agricultural GDP	CNY 100 million
		Grain yield	10,000 tons
	Undesirable output	Agricultural carbon emissions	10,000 tons

(2) Industrial sector

Similarly, the number of employees, capital stock (CNY), and industrial water consumption (m^3) are selected as input variables. The real GDP (CNY) and chemical oxygen demand (COD) emissions (ton) from wastewater are selected as desirable outputs and undesirable outputs, respectively (Table 2).

Table 2. Input–output index system in industrial WRUE.

Indicator	Name	Index	Units
Input indicators	Labor	Number of employees	10,000 people
	Capital	Capital stock	CNY 100 million
	Water resources	Industrial water consumption	100 million m^3
Output indicators	Desirable output	Industrial GDP	CNY 100 million
	Undesirable output	Industrial COD emissions	tons

2.2.2. Tobit Regression Variables

Based on previous research and referring to the literature [20,31,46], the driving factors of WRUE are considered from the following aspects: (1) industrial structure: primary industrial proportion (%) and secondary industrial proportion (%); (2) economic level: per capita GDP (CNY); (3) water resources: water resources endowment (m^3), groundwater proportion (%), utilization rate of water (%), and industrial water proportion (%); (4) influence of the government: financial support (proportion of regional financial expenditure on science and technology, %) and R&D intensity (proportion of R&D expenditure to GDP, %); (5) environmental protection: environmental regulation (proportion of completed investment in pollution control to GDP, %); (6) in the agricultural sector: the agricultural planting area (hectares) are added; (7) in the industrial sector: the urbanization rate (%) is added. The definitions and descriptions of variables are shown in Tables 3–5. Given the existence of ratio-type variables and numerical variables in factors, to make the data comparable, the numerical data are firstly logarithmically processed.

Table 3. Definition and description of variables in China.

X	Variable Name	Variable Definition	Units
X_1	Tertiary industrial proportion	Tertiary industrial GDP/total GDP	%
X_2	Level of opening up	Total import and export volume	1000 dollars
X_3	Economic level	Per capita GDP	CNY
X_4	Water resources endowment	Per capita water resources	m^3
X_5	Agricultural water proportion	Agricultural water consumption/total water consumption	%
X_6	Population	Total population at the end of the year	people
X_7	Urbanization rate	Proportion of urban population	%
X_8	Financial support	Proportion of regional financial expenditure on science and technology	%

Table 4. Definition and description of variables in agricultural sector.

X	Variable Name	Variable Definition	Units
X_1	Primary industrial proportion	Agricultural GDP/total GDP	%
X_2	Secondary industrial proportion	Industrial GDP/total GDP	%
X_3	Economic level	Per capita GDP	CNY
X_4	Water resources endowment	Per capita water resources	m^3/
X_5	Groundwater proportion	Groundwater supply/total water supply	%
X_6	Effective irrigated area	Effective irrigated area	1000 hectares
X_7	Agricultural planting area	Sown area of grain crops	1000 hectares
X_8	Financial support	Proportion of national financial expenditure on agriculture, forestry and water affairs	%
X_9	Environmental regulation	Proportion of completed investment in pollution control to GDP	%

Table 5. Definition and description of variables in industrial sector.

X	Variable Name	Variable Definition	Units
X_1	Primary industrial proportion	Agricultural GDP/total GDP	%
X_2	Secondary industrial proportion	Industrial GDP/total GDP	%
X_3	Economic level	Per capita GDP	CNY
X_4	Water resources endowment	Per capita water resources	m^3
X_5	Utilization rate of water	Total water consumption/total water resources	%
X_6	Industrial water proportion	Industrial water consumption/total water consumption	%
X_7	Urbanization rate	Proportion of urban population	%
X_8	R&D intensity	Proportion of R&D expenditure to GDP	%
X_9	Environmental regulation	Proportion of completed investment in pollution control to GDP	%

2.2.3. Data

The data are obtained from the China Statistical Yearbook and the statistical yearbooks published by the official of the regional statistical bureaus. The economic-related data are all processed with 2005 as the base period.

The data on agricultural carbon emissions are calculated by combining the methodology in the recommended guidelines of the Intergovernmental Panel on Climate Change (IPCC) and the study of Hu et al. [47]. The capital stock data of the secondary industry are calculated by the "perpetual inventory method" mentioned by Zhang et al. [48].

3. Results

Inter-provincial WRUE from 2005 to 2021 in China was measured with the SE-SBM model. The WRUE of the agricultural and industrial sectors was also measured separately. The WRUE results for the industrial sector are up to 2020.

3.1. WRUE Measurement Results

3.1.1. Overall Results of WRUE in China

The WRUE results are shown in Table 6. Given the space limitation, not all results up to 2015 have been listed. The average inter-provincial WRUE in China ranges from 1.156 in Beijing, the highest, to 0.501 in Ningxia, the lowest. In Beijing, Tianjin, Shanghai, and Guangdong, some WRUE values are greater than 1. This is a further distinction of the efficiency level of effective DMUs when they are evaluated as effective in the SBM. This is the advantage of "super-efficiency" in the SE-SBM.

Table 6. WRUE of China.

Province	Year									Mean
	2005	**2010**	**2015**	**2016**	**2017**	**2018**	**2019**	**2020**	**2021**	
Beijing	1.212	1.198	1.154	1.061	1.211	1.065	1.062	1.142	1.168	1.156
Tianjin	1.023	1.028	1.081	1.183	1.068	1.104	1.097	1.116	1.108	1.055
Hebei	0.714	0.659	0.604	0.632	0.553	0.599	0.600	0.526	0.515	0.625
Shanxi	0.701	0.623	0.593	0.584	0.555	0.590	0.588	0.528	0.536	0.613
Inner Mongolia	0.658	0.632	0.623	0.675	0.658	0.757	0.769	0.573	0.567	0.648
Liaoning	0.658	0.633	0.610	0.652	0.601	0.659	0.677	0.555	0.562	0.626
Jilin	0.656	0.611	0.578	0.662	0.598	0.640	0.645	0.545	0.535	0.612
Heilongjiang	0.698	0.650	0.595	0.631	0.598	0.622	0.607	0.537	0.552	0.630
Shanghai	1.059	1.069	1.094	1.101	1.107	1.111	1.111	1.107	1.100	1.084
Jiangsu	0.808	0.734	0.725	0.663	0.628	0.663	0.660	0.604	0.610	0.715
Zhejiang	0.713	0.747	0.711	0.685	0.637	0.714	0.713	0.601	0.597	0.700
Anhui	0.664	0.613	0.552	0.557	0.509	0.508	0.494	0.452	0.452	0.568
Fujian	0.731	0.693	0.642	0.625	0.568	0.600	0.603	0.566	0.570	0.655
Jiangxi	0.655	0.604	0.541	0.530	0.489	0.474	0.469	0.458	0.458	0.559
Shandong	0.799	0.740	0.665	0.700	0.636	0.715	0.712	0.591	0.588	0.698
Henan	0.740	0.654	0.611	0.636	0.571	0.616	0.613	0.507	0.502	0.631
Hubei	0.672	0.638	0.594	0.596	0.546	0.563	0.561	0.470	0.477	0.601
Hunan	0.659	0.632	0.574	0.593	0.558	0.547	0.532	0.481	0.481	0.593
Guangdong	1.063	1.058	0.714	0.729	0.658	0.669	0.661	0.580	0.585	0.856
Guangxi	0.631	0.602	0.553	0.544	0.490	0.464	0.445	0.422	0.423	0.555
Hainan	0.642	0.630	0.534	0.558	0.503	0.493	0.490	0.441	0.449	0.564
Chongqing	0.656	0.642	0.637	0.716	0.667	0.760	0.756	0.558	0.552	0.654
Sichuan	0.647	0.624	0.588	0.598	0.556	0.555	0.540	0.479	0.479	0.593
Guizhou	0.633	0.610	0.549	0.530	0.474	0.456	0.438	0.400	0.388	0.548
Yunnan	0.670	0.636	0.582	0.583	0.544	0.568	0.538	0.430	0.426	0.589
Xizang	0.663	0.582	0.578	0.493	0.444	0.427	0.409	0.401	0.403	0.552
Shaanxi	0.663	0.629	0.599	0.632	0.556	0.612	0.609	0.505	0.497	0.610
Gansu	0.639	0.607	0.522	0.563	0.516	0.553	0.556	0.448	0.449	0.568
Qinghai	0.594	0.570	0.516	0.511	0.494	0.497	0.501	0.462	0.460	0.542
Ningxia	0.557	0.537	0.470	0.459	0.448	0.448	0.449	0.443	0.444	0.501
Xinjiang	0.630	0.603	0.535	0.504	0.484	0.479	0.478	0.443	0.440	0.552
Mean	0.726	0.693	0.643	0.651	0.610	0.630	0.625	0.560	0.560	0.660

3.1.2. Agricultural WRUE

The agricultural WRUE results are shown in Table 7 and Figure 1.

Table 7. Agricultural WRUE.

Province	Year									Mean
	2005	2010	2015	2016	2017	2018	2019	2020	2021	
Beijing	1.119	1.124	1.102	1.084	1.071	1.034	1.028	1.052	1.083	1.077
Tianjin	0.666	0.757	0.809	0.921	1.035	1.086	1.093	1.115	1.125	0.956
Hebei	0.688	0.825	0.865	0.899	0.911	0.920	0.920	0.977	0.973	0.886
Shanxi	0.766	0.766	0.788	0.790	0.842	0.863	0.811	0.858	0.827	0.812
Inner Mongolia	0.873	0.775	0.799	0.788	0.779	0.814	0.793	0.787	0.762	0.797
Liaoning	1.043	0.941	1.083	1.071	1.085	1.097	1.120	1.093	1.108	1.071
Jilin	1.188	1.151	1.174	1.219	1.227	1.209	1.227	1.129	1.142	1.185
Heilongjiang	1.054	1.163	1.173	1.161	1.157	1.191	1.214	1.197	1.179	1.165
Shanghai	1.135	1.261	1.166	1.034	1.019	1.199	1.093	1.062	1.035	1.112
Jiangsu	0.874	0.988	1.058	1.063	1.073	1.069	1.062	0.947	0.949	1.009
Zhejiang	0.864	0.774	0.775	0.838	1.023	1.067	1.073	1.075	1.070	0.951
Anhui	0.701	0.765	0.830	0.825	0.833	0.801	0.781	0.791	0.768	0.788
Fujian	0.770	0.779	0.731	0.778	0.885	0.866	0.880	1.007	1.016	0.857
Jiangxi	0.867	0.883	0.939	0.953	0.964	0.979	0.975	0.990	0.977	0.947
Shandong	0.855	0.847	1.000	1.005	1.020	1.037	1.027	1.058	1.086	0.993
Henan	1.049	1.023	1.099	1.091	1.109	1.137	1.123	1.198	1.138	1.107
Hubei	0.788	0.733	0.750	0.748	0.760	0.810	0.786	0.799	0.783	0.773
Hunan	0.862	0.892	0.879	0.876	0.864	0.864	0.852	0.863	0.851	0.867
Guangdong	1.017	1.009	0.937	0.961	1.012	1.007	1.016	1.038	1.037	1.004
Guangxi	0.738	0.738	0.698	0.681	0.674	0.710	0.689	0.701	0.686	0.702
Hainan	1.128	1.170	1.160	1.143	1.146	1.146	1.139	1.142	1.143	1.146
Chongqing	1.279	1.272	1.118	1.105	1.102	1.108	1.099	1.091	1.086	1.140
Sichuan	1.011	0.962	0.969	1.001	1.010	1.021	1.008	1.024	1.013	1.002
Guizhou	1.050	1.005	0.992	1.008	1.026	1.016	1.043	1.044	1.065	1.028
Yunnan	0.804	0.781	0.741	0.731	0.738	0.866	0.851	0.895	0.907	0.813
Xizang	1.267	1.140	1.025	0.875	0.946	1.035	1.031	1.040	1.046	1.045
Shaanxi	0.716	0.777	0.761	0.785	0.768	0.793	0.798	0.825	0.812	0.782
Gansu	0.801	0.776	0.763	0.786	0.859	0.921	0.898	0.867	0.869	0.838
Qinghai	0.802	0.723	0.664	0.767	0.780	0.812	1.012	1.050	1.096	0.856
Ningxia	0.682	0.684	0.660	0.691	0.681	0.711	0.680	0.710	0.682	0.687
Xinjiang	0.855	0.790	0.805	0.734	0.743	0.742	0.763	0.748	0.760	0.771
Mean	0.913	0.912	0.913	0.916	0.940	0.966	0.964	0.973	0.970	0.941

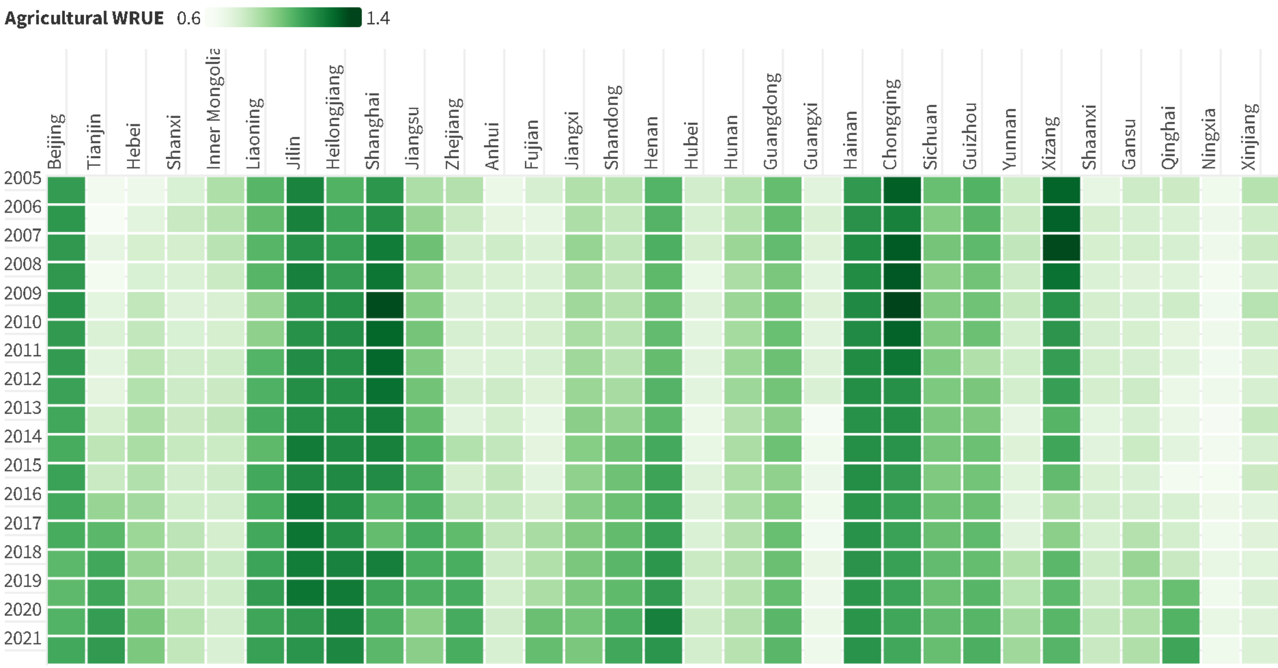

Figure 1. Agricultural WRUE.

The mean value of agricultural WRUE in China was above 0.9 from 2005 to 2021. The highest value was Jilin (1.185), indicating that Jilin was better matched in terms of fertilizers, machinery, labor, and water resources. The lowest mean value was Ningxia (0.687), which is in the arid inland areas of Northwestern China. The inefficiency indicates the mismatch between agricultural activities in economic layout and water use [49].

3.1.3. Industrial WRUE

The industrial WRUE results are shown in Table 8 and Figure 2.

Table 8. Industrial WRUE.

Province	Year								Mean
	2005	2010	2015	2016	2017	2018	2019	2020	
Beijing	1.459	1.468	1.480	1.237	1.251	1.277	1.302	1.305	1.399
Tianjin	1.112	1.162	1.155	1.150	1.116	1.082	1.070	1.200	1.152
Hebei	0.453	0.365	0.318	0.311	0.314	0.311	0.298	0.315	0.362
Shanxi	0.435	0.356	0.291	0.280	0.286	0.290	0.306	0.348	0.352
Inner Mongolia	1.048	1.157	1.083	1.086	1.082	1.087	1.112	1.023	1.101
Liaoning	0.466	0.409	0.408	0.365	0.382	0.395	0.398	0.464	0.429
Jilin	0.369	0.315	0.298	0.296	0.309	0.299	0.300	0.421	0.334
Heilongjiang	0.465	0.387	0.360	0.357	0.356	0.335	0.330	0.363	0.393
Shanghai	1.075	0.692	1.037	1.046	1.086	1.072	1.047	1.040	0.998
Jiangsu	0.387	0.310	0.306	0.282	0.284	0.270	0.260	0.294	0.323
Zhejiang	0.380	0.318	0.327	0.320	0.326	0.320	0.314	0.333	0.339
Anhui	0.268	0.186	0.181	0.171	0.171	0.161	0.153	0.188	0.197
Fujian	0.391	0.317	0.299	0.280	0.286	0.275	0.282	0.350	0.326
Jiangxi	0.306	0.196	0.187	0.176	0.175	0.168	0.161	0.190	0.212
Shandong	1.025	0.568	0.510	0.457	0.472	0.434	0.423	0.459	0.607
Henan	0.422	0.282	0.257	0.255	0.256	0.252	0.266	0.326	0.304
Hubei	0.262	0.274	0.264	0.257	0.260	0.247	0.237	0.225	0.269
Hunan	0.298	0.249	0.234	0.223	0.228	0.218	0.209	0.233	0.252
Guangdong	1.008	0.399	0.394	0.375	0.372	0.360	0.345	0.367	0.515
Guangxi	0.306	0.220	0.227	0.227	0.224	0.207	0.194	0.180	0.236
Hainan	0.324	0.334	0.296	0.288	0.287	0.276	0.267	0.310	0.314
Chongqing	0.294	0.258	0.278	0.273	0.280	0.262	0.254	0.310	0.277
Sichuan	0.266	0.246	0.280	0.264	0.266	0.264	0.263	0.338	0.277
Guizhou	0.284	0.211	0.213	0.207	0.210	0.205	0.199	0.191	0.219
Yunnan	0.373	0.262	0.289	0.286	0.292	0.293	0.280	0.279	0.298
Xizang	0.401	0.263	0.272	0.223	0.218	0.215	0.200	0.395	0.287
Shaanxi	0.412	0.333	0.414	0.410	0.407	0.418	0.400	0.387	0.403
Gansu	0.278	0.222	0.211	0.206	0.201	0.201	0.203	0.251	0.233
Qinghai	0.246	0.249	0.261	0.270	0.275	0.275	0.260	0.276	0.261
Ningxia	0.257	0.257	0.242	0.237	0.235	0.242	0.239	0.210	0.247
Xinjiang	0.557	0.371	0.317	0.304	0.301	0.301	0.281	0.308	0.389
Mean	0.504	0.408	0.409	0.391	0.394	0.387	0.382	0.415	0.429

In the industrial sector, WRUE ranges from the highest of 1.399 in Beijing to the lowest of 0.212 in Jiangxi. The average WRUE is 0.429 during 2005–2020 in the industrial sector, with a declining trend. This suggests that China's rapid economic growth over the period was based on low industrial WRUE. There was an average annual decrease of 4.16% from 2005 to 2010 and 1.84% after 2011. The slowdown in efficiency reduction is indicative of China's sustainable development efforts.

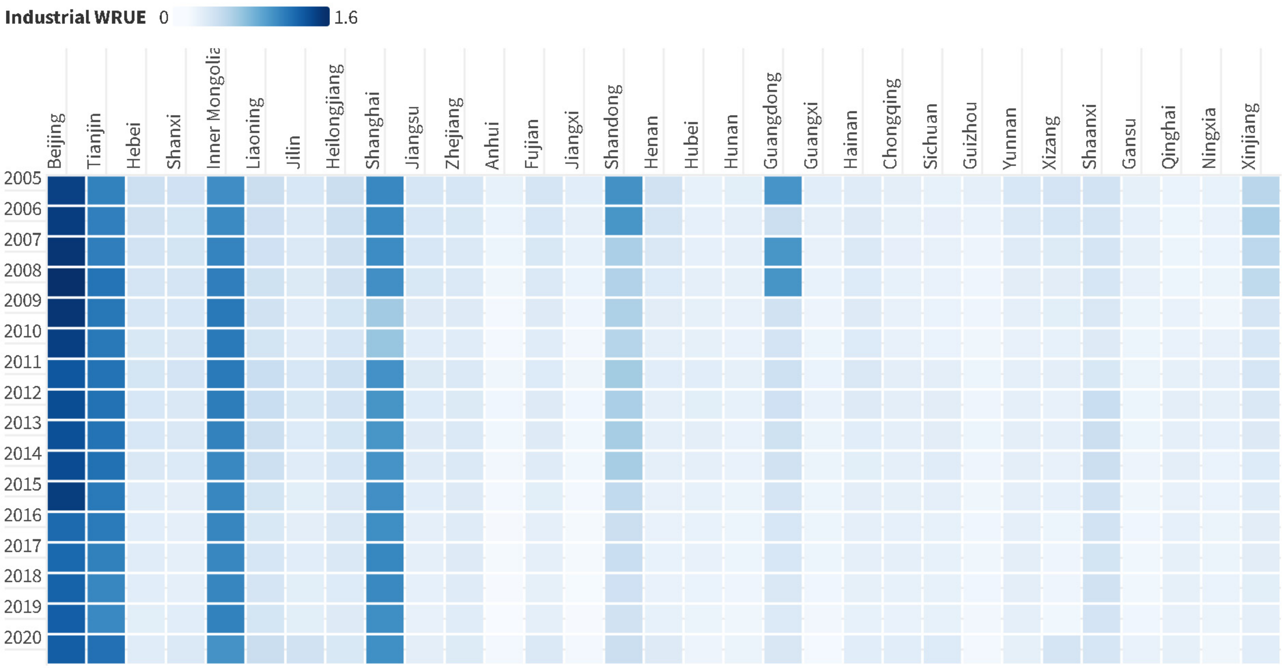

Figure 2. Industrial WRUE.

3.2. Driving Factors

The results of Tobit regression are shown in Tables 9–11.

The overall driving factors result of WRUE in China (Table 9).

Table 9. Tobit regression result of driving factors in China.

X	Variable Name	Regression Coefficient	Standard Deviation
X_1	Tertiary industrial proportion	−0.00085	0.0039398
X_2	Level of opening up	−0.0173821	0.0477747
X_3	Economic level	0.3056228 ***	0.0984446
X_4	Water resources endowment	−0.034023	0.0338003
X_5	Agricultural water proportion	−0.0141513 ***	0.0032433
X_6	Population	−0.1791625 **	0.083117
X_7	Urbanization rate	−0.017255 **	0.0070058
X_8	Financial support	0.0650491 **	0.0294161
C	Constant term	1.271306 *	0.7247596

Note: *, **, *** indicate significant at the 10%, 5% and 1% levels, respectively.

The WRUE driving factors result in agricultural sector (Table 10).

Table 10. Tobit regression result of driving factors in agricultural sector.

X	Variable Name	Regression Coefficient	Standard Deviation
X_1	Primary industrial proportion	−0.0007142	0.0019784
X_2	Secondary industrial proportion	−0.0050987 ***	0.0006222
X_3	Economic level	0.0175212	0.0113597
X_4	Water resources endowment	−0.0049376	0.0091182
X_5	Groundwater proportion	−0.1183793 *	0.0671602
X_6	Effective irrigated area	−0.1469869 ***	0.0260604
X_7	Agricultural planting area	0.1446299 ***	0.0202212
X_8	Financial support	−0.0040641 **	0.0017402
X_9	Environmental regulation	−0.0270033 ***	0.0098143
C	Constant term	1.041346 ***	0.1827509

Note: *, **, *** indicate significant at the 10%, 5% and 1% levels, respectively.

The WRUE driving factors result in industrial sector (Table 11).

Table 11. Tobit regression result of driving factors in industrial sector.

X	Variable Name	Regression Coefficient	Standard Deviation
X_1	Primary industrial proportion	−0.0013346	0.0025046
X_2	Secondary industrial proportion	0.0036085 ***	0.0009079
X_3	Economic level	−0.0724771 ***	0.0198431
X_4	Water resources endowment	−0.0152294	0.014615
X_5	Utilization rate of water	−0.0002677 ***	0.000101
X_6	Industrial water proportion	−0.0040386 ***	0.0011027
X_7	Urbanization rate	0.003648 **	0.0016135
X_8	R&D intensity	−0.0415154 ***	0.0146881
X_9	Environmental regulation	−0.0086181	0.0113406
C	Constant term	1.124456 ***	0.2088492

Note: **, *** indicate significant at the 5% and 1% levels, respectively.

4. Discussion

In the agricultural sector, the average WRUE reached over 1.0 in Beijing, Shanghai, Hainan, Heilongjiang, Jilin and Liaoning. As in the industrial sector, developed provinces and cities pay more attention to urban pollution and resource intensification issues. Therefore, the industrial WRUE of such provinces as Beijing, Tianjin, and Shanghai is basically above 1.0. In the less developed regions, there is still a need for water-intensive enterprises to promote economic growth. The industrial WRUE in these regions has been made to be inefficient, with all of them below 0.3.

Based on the Tobit regression results, the driving factors of WRUE change are discussed as follows.

4.1. Economic Structure and Level

The share of the industrial sector is significantly negatively correlated with water efficiency in agriculture, and positively correlated with industrial water efficiency. The regression coefficients are −0.0050987 and 0.0036085, respectively. An increase in the share of the industrial sector usually means a lower share of agriculture in GDP and better economic development. This confirms that the scale effect also exists in the efficient use of industrial water. Whereas, as a whole, the level of economic development positively drives WRUE. The agglomeration effect of industry, higher levels of management and technology, better water protection policies, and infrastructure investments in wastewater treatment all contribute to efficiency.

The negative relationship with the coefficient of −0.0724771 between the economic level and industrial WRUE deserves attention. This may be attributed to the fact that with the economy developing, the share of the tertiary sector increases and the weight of industry decreases. The reduction in the size of industry makes the sector less efficient in water use, which is also in line with the previous scale effect. There is no doubt that economic development is conducive to the efficient use of water. However, in the economic growth driven by the tertiary sector, the problem of declining industrial water efficiency cannot be ignored.

4.2. Water Resources Endowment

Water resources endowment is negatively correlated with WRUE in both agriculture (−0.0049376) and industry (−0.0152294) with P not being significant at 10% (0.31 in the whole, 0.58 in agriculture, 0.29 in industry). This suggests an underlying tendency for water scarcity areas to use water more efficiently than water-abundant areas. The proportion of groundwater in total water consumption is significantly negatively correlated (−0.1183793) with agricultural WRUE.

A high share of groundwater use in agricultural production usually implies a poor water endowment. It means that results, after taking into account for agricultural carbon emissions, provide evidence to the contrary. In other words, after accounting for agricultural carbon emissions, agricultural water efficiency in water-scarce areas will be lower than in water-abundant areas.

Similarly, in industry, the higher the proportion of water resources exploited is, the poorer will be the water endowment. At this point, the industrial WRUE after considering the industrial COD emissions is lower in water-scarce areas.

This is a result that diverges from common sense and previous research. This result indicates that the relationship between water resources endowment and WRUE needs to be further studied, given that climate change and environmental protection are increasingly concerned [50].

4.3. Government Influence and Environmental Regulations

Government financial support positively (0.0650491) promotes the overall WRUE. However, the negative (−0.0040641) impact of government investment in agriculture, forestry and water affairs on agricultural WRUE is of great concern. The maintenance and construction of new water conservancy facilities are believed to improve the efficiency of irrigation water use [51]. This view is challenged by the negative impact of government financial support for agriculture on WRUE. This becomes reasonable when the focus of financial support is on ensuring the total water supply and output in agriculture, rather than on water-saving facilities. Government financial support for agriculture should raise the concern for agricultural water conservancy in order to avoid excessive waste of precious water resources and improve water efficiency. A similar situation also occurs in the industrial sector. The increase in R&D intensity reduces industrial WRUE. It shows that the focus of R&D is not on energy conservation and resource efficiency, but on other aspects. This coincides with the fact that China's industry has not yet reached the stage of high-quality development. Whether it is agriculture or industry, on the path of green and sustainable development, financial support should encourage more efficient use of resources.

Unsurprisingly, environmental regulations have had a negative impact (−0.0270033 in agriculture, −0.0086181 in industry) on water efficiency [52]. The reason is clear: environmental protection has increased the cost of production. However, this is not a reason to relax environmental regulations. On the contrary, it confirms that government financial support should increase investment in the green ecological development of agriculture and industry.

4.4. Non-Shared Factors between Agriculture & Industry

In the agricultural sector, the effective irrigation area and the sown area of grain crops have a negative (−0.1469869) and positive (0.1446299) impact on agricultural water resources, respectively. It is clear that more sown area of grain crops will increase agricultural water use. However, the scale effect of agricultural cultivation has improved WRUE. The effective irrigation area is also closely related to agricultural water consumption. More agricultural water use leads to a decrease in efficiency, confirming low irrigation efficiency in China. This is consistent with China's low level of water-saving irrigation construction. Promoting water-saving irrigation is an important way to improve the WRUE in the agricultural sector.

The urbanization rate and industrial WRUE are significantly positively correlated, with a coefficient of 0.00364. China's urbanization rate rose from 43.0% to 64.7% between 2005 and 2021. The high urbanization rate has led to a rapid increase in the total amount of domestic and industrial water use, accompanied by increasing industrial WRUE [53]. The positive relationship indicates that high urbanization rates have been able to eliminate negative impacts through organizational coordination and technological progress. It shows that China's urbanization construction is in the stage of high-quality. Organizational advantages and scientific and technological means have been utilized to achieve ecological and green development of efficient use of resources.

5. Conclusions

This paper firstly measures the WRUE of agriculture and industry in China with the SE-SBM model, considering agricultural carbon emissions and industrial pollution as undesirable outputs. Then, the Tobit regression is applied to discuss the driving factors of WRUE in the agricultural and industrial sectors.

The main conclusions are as follows: (1) Economic development is conducive to the improvement of overall WRUE. The higher the proportion of industry there is in the economy, the higher will be the industrial WRUE. There is a scale effect in industrial WRUE. When the proportion of the tertiary industry in the economic structure increases and the industrial proportion decreases, the WRUE will be negatively affected. (2) The agricultural WRUE of the areas with poor water endowment is lower than that of the areas with abundant water resources. Similarly, industrial WRUE in water-scarce areas is lower than that in water-rich areas. Today, ecological development has received great attention and the relationship between water resources endowment and WRUE needs to be further studied. (3) Government financial support positively promotes the WRUE. However, the failure of agricultural financial support to improve agricultural WRUE indicates that investment in water-saving irrigation construction is still insufficient. R&D investment in industry has not improved industrial WRUE. (4) The scale of agricultural planting has a positive driving effect on agricultural WRUE. Agricultural production also has scale effects on the WRUE. However, the agricultural WRUE will decline as the effective irrigated area increases. Irrigation in China is inefficient. The urbanization rate plays a positive role in industrial WRUE. China's urbanization needs to continue to be focused on quality.

The policy implications are as follows: (1) High-quality economic development needs to be upheld. Precautionary measures need to be taken to prevent the inefficient use of resources from being neglected as the industrial sector declines in economic development. (2) From the perspective of green ecology, the relationship between water endowment and WRUE needs to be further studied. (3) Financial support for agricultural and industrial ecological development needs to be increased. In agriculture, more support should be given to water-saving irrigation construction. In industry, energy conservation and efficient use of resources should be the focus. (4) Urbanization should pay attention to high-quality development. We should be making use of organizational advantages and scientific and technological means to achieve ecological and green development of efficient use of resources.

This paper has limitations. The study depends on inter-provincial and annual data. With the rise in big data applications, the exploration of WRUE-driving factors at scales such as the city or county requires future research.

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