

Article

China's Water Utilization Efficiency: An Analysis with Environmental Considerations

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Abstract: This paper estimates China's water utilization efficiency using the directional distance function to take into account the environmental degradation affecting the economy. We further analyze the spatial correlation and the factors influencing the utilization efficiency using spatial panel data models. The results show that water utilization efficiency in China differs between provinces and regions. For example, water utilization efficiency in the eastern coastal provinces is significantly higher than that of inland provinces. The pattern of spatial auto-correlation Moran's I index presents significant spatial auto-correlation and evident cluster tendencies in China's inter-provincial water utilization. Factors that contribute to water utilization efficiency include economic development, technological progress, and economic openness. Negative factors affecting water utilization efficiency arise from industrial structure, government interference, and water resources endowment. In addition, the price of water resources is insignificant. The improvement of water utilization efficiency is essential to sustainable economic development. To raise the utilization efficiency of water resources, China should focus on transforming its industrial restructure, advancing technological development, enhancing economic openness, and encouraging entrepreneurial innovations. Moreover, establishing a mechanism to encourage water conservation and reduce wastewater pollution will further increase water utilization efficiency.

Keywords: water utilization efficiency; environmental degradation; spatial panel data models; directional distance function

1. Introduction

Resources utilization efficiency means using fewer resources to produce the same amount of goods and services, or using a given amount of resources to produce more output or better quality of life [1]. We estimate water utilization efficiency in China taking the environmental degradation of water utilization into consideration. This means minimizing the water input given a certain level of "green output" (economic output subtracting environmental damages). Currently there are two major water resources problems in China: water resource shortages and water ecological degradation. Water resources per capita in China are about 2200 m³, only a quarter of the world average, with an extremely unequal distribution [2]. According to *China Water Resources Bulletin*, in 2010, the country's sewage discharge is 792×108 t, a 36% increase from 1997—a phenomenon seemingly contradicting the water shortage problem. With rapid economic growth and the ever-rising population, improving water utilization efficiency has become an essential step toward sustainable economic growth in China. This paper estimates China's water utilization efficiency using the directional distance function with eco-environmental considerations. We further analyze the factors influencing the utilization efficiency

by applying spatial panel data models. This paper seeks to provide a theoretical support for sustainable utilization of water resources in China.

2. Literature Review

2.1. Studies of Utilization Efficiency of Water Resources: Industrial, Agricultural, and Urban

Sustainable utilization of water resources is the cornerstone for sustainable economic growth. Improving water utilization efficiency and building a society characterized by water conservation and low pollution have been the focus of the global community. Allan [3], Zoebl [4], and Berger *et al.* [5] consider that improving utilization efficiency is an effective solution to the water shortage problem. Studying utilization efficiency of agricultural water, Barker [6] and Lilienfeld *et al.* [7] separate irrigation efficiency into irrigation water transfer efficiency and field utilization efficiency. High irrigation efficiency does not necessarily reflect efficient management. Dbehibl [8] finds an improvement of irrigation efficiency of a single field does not always imply an improvement in a river basin's productive capacity. Thus he [8] suggests studying macro-level utilization efficiency for agricultural water. Regarding the utilization efficiency of industrial water, Walsh [9] analyzed industrial water consumption and industrial output in the Netherlands from the 1970s to the 1990s. He finds that industrial water consumption first grew steadily and then significantly decreased; however industrial production grew nearly three times during the same period. Mortier *et al.* [10] analyzed the water management plan of the Flemish steel industry. They found that the improving techniques in obtaining water, cooling water, and environmental protection effectively raised the utilization efficiency of industrial water. Novotny [11] studied industrial water usage in the US and found that industrial water consumption fell by 32% due to technological advances in production. Studying the ecological value of water resources, Capello [12] and Oh *et al.* [13] evaluated the urban water utilization efficiency of Italy and the USA, respectively. They believe that water carrying capacity should be considered in urban development as that directly affects urban sustainability.

Water usage can produce undesirable output that significantly impacts an evaluation of efficiency. Economic efficiency requires taking environmental considerations into account so that inaccurate or incomplete water resource management is avoided. To achieve the optimal measure of water utilization efficiency, it is important to take into consideration the undesirable outputs such as water pollution [14]. Among studies on environmental efficiency taking undesirable output into account some assume the production technology is fixed then analyze the pollutant problem. These studies treat pollution as an input [15] or view pollution as a negative output [16]. Some studies focus on the improvement of production technology, that is, expanding traditional production technology to encompass environmental production technology [17]. Other studies [18] convert the strong disposability of desirable output and undesirable output into weak disposability. This kind of conversion regards undesirable output as the opportunity cost of environmental regulation.

2.2. Studies of Data Envelopment Analysis in Environmental Research

Data Envelopment Analysis (DEA) has been widely used to estimate environmental performance. Zhou *et al.* [19] integrate DEA efficiency measures with the concept of environmental DEA technology to estimate total factor carbon emission performance of 18 countries. Fare *et al.* [20] used DEA techniques to compute an index of environmental performance that simultaneously takes into account inputs used, and the good outputs and undesirable outputs produced. Wu *et al.* measured China's industrial energy efficiency using several environmental DEA models accounting for CO₂ emissions [21]. Valadkhani [22] adopted a multiplicative extension of environmental DEA models to measure environmental efficiency changes of the world's major polluters. Shi *et al.* [23] measured industrial energy efficiency and the maximum energy-saving potential of 28 administrative regions in China. Although DEA models accounting for undesirable outputs are often adopted in energy and environmental research, they are rarely used in measuring water utilization efficiency. Our paper

estimates water utilization efficiency using a DEA model that takes into account of both the desirable and the undesirable outputs.

2.3. Studies of Factors Influencing the Utilization Efficiency of Water Resources

2.3.1. Agricultural Water

Because of the importance of agricultural water and food security, many researches study the factors influencing the utilization efficiency of agricultural water. Using a stochastic frontier analysis based on the Cobb-Douglas (C-D) production function, Mcgoekin *et al.* [24] and Omezzine and Zaibet [25] analyze the positive effect that water-conserving technologies had on the utilization efficiency of irrigation water. The technologies they studied included soil moisture sensors and business plans. Using China's provincial statistics from 1999 to 2002, Karagiannis [26] also used a C-D stochastic frontier production function to measure the utilization efficiency of irrigation water. He found that natural conditions such as climate and soil plus infrastructure conditions, such as irrigation and water conservation, are the main factors influencing the utilization efficiency of irrigation water. Based on survey data for sixty farmers in Zeerust, South Africa, Dhehibl [8] estimated the utilization efficiency of irrigation water using the DEA methodology. He shows that arable land, land ownership, irrigation methods, irrigation project types, and planting structure all significantly affect the utilization efficiency of irrigation water positively.

2.3.2. Industrial Water

Research of utilization efficiency of water resources has shifted from agricultural to industrial water. There has also been a transition from water engineering efficiency evaluation to economic efficiency evaluation [27,28]. Li *et al.* [29] analyzed water utilization efficiency in production processes in China and concluded that the adoption of technology can help improve utilization efficiency and water conservation. Rogers *et al.* [30] considered water as an economic good, implying changes in the price of water can have an impact on utilization efficiency. Bolong [31] and Sojamo [32] discovered that in addition to technology and the price of water, industrial structure and economic openness can also have a significant impact on utilization efficiency. Sun *et al.* [33] analyzed the characteristics, the patterns, and the factors influencing the spatial and temporal disparities in water utilization efficiency in China. However, this is without considering environmental factors.

Utilization efficiency studies have expanded from single-factor efficiency measures to total-factor efficiency measures, from irrigation water utilization to basin-wide water utilization, from agricultural water to comprehensive water efficiency combining agricultural water, industrial water, and urban water. However, few studies of water utilization efficiency incorporate environmental degradation in their analysis. It is also the case that little research has focused on the dynamic changes and spatial differences in the utilization efficiency of China's inter-provincial water resources. This paper estimates comprehensive water utilization efficiency for thirty provinces in China by incorporating environmental degradation into the directional distance function analysis. We then provide some suggestions for improving this comprehensive utilization efficiency of China's water resources.

3. Methodology and Data

3.1. Directional Distance Function

Charnes *et al.* proposes using DEA to measure "decision making efficiency" [34]. A DEA model is a useful tool to measure relative efficiency when evaluating a number of decision making units that consist of the same inputs and outputs. However, traditional DEA models are not equipped to measure efficiency when the production function consists of desirable and undesirable outputs. The direction distance function provides a solution to such an issue [35].

Directional distance function linking input factors to desirable and undesirable outputs is defined as “environmental technology” by Chung *et al.* [17]. This environmental technology function differs from traditional input-output models. For an environmental technology structure, given fixed amounts of input, investing in water purification equipment is needed to reduce pollution. This means there will be fewer inputs for the production of desirable goods accompanying the reduction of undesirable goods. Adopting this concept, we construct the environmental production function for water resources:

$$P(x) = \{(y, b) : x \text{ can produce } (y, b)\}, x \in R_+^N \quad (1)$$

$P(x)$ is the production function of the “desirable output” and the associated “undesirable output”. Outputs are produced by N kinds of input resource x . $x = (x_1, x_2, \dots, x_n)$ represents the input vector; $y = (y_1, y_2, \dots, y_m)$ is the desirable output vector, and $b = (b_1, b_2, \dots, b_j)$ is the undesirable output vector, mainly pollutant discharges during the production processes, such as waste water and exhaust fuel.

The production function $P(x)$ has four possible forms: (1) jointly weak disposability; (2) strong free disposability of desirable output; (3) free disposability of input factors; (4) weak disposability of output.

Using the directional vector $g = (g_y, -g_b)$, we construct the directional environmental output distance function based on the shortage function created by Luenberger [36]:

$$\vec{D}_0^t(y^t, x^t, b^t; g_y, -g_b) = \sup [b : (y^t + bg_y, b^t - bg_b) \in p^t(x^t)] \quad (2)$$

In this function, $\vec{D}_0^t(y^t, x^t, b^t; g_y, -g_b)$ is the directional environmental output distance function; the desirable output y and the undesirable output b are treated equally as the output. For a given input x , when output y and pollution b increase or decrease in the same proportion, β is the largest possible coefficient for minimizing pollution b and maximizing output y . Therefore, the value of directional distance function is that it measures the gap between actual production and the optimal production frontier. This is similar to the traditional definition of technology efficiency. Environmental technology efficiency can be measured by the ratio of the actual amount of the desirable output ($y_{k'}^t$) and the frontier output under the environmental technology structure $((1 + \beta) \times y_{k'}^t)$:

$$ETE(y_{k'}^t, x_{k'}^t, b_{k'}^t; y_{k'}^t, -b_{k'}^t) = \frac{1}{1 + \vec{D}_0^t(y_{k'}^t, x_{k'}^t, b_{k'}^t; y_{k'}^t, -b_{k'}^t)} \quad (3)$$

$$\begin{aligned} \vec{D}_0^t(y_{k'}^t, x_{k'}^t, b_{k'}^t; y_{k'}^t, -b_{k'}^t) &= \max \beta \\ \text{s.t. } \sum_{k=1}^K z_k^t y_{k,m}^t &\geq (1 + \beta) y_{k',m}^t \\ \sum_{k=1}^K z_k^t b_{k,j}^t &= (1 - \beta) b_{k',j}^t \\ \sum_{k=1}^K z_k^t x_{k,n}^t &\leq x_{k',n}^t \\ z_k^t &\geq 0 \\ m &= 1, 2, \dots, M; j = 1, 2, \dots, J; n = 1, 2, \dots, N; k = 1, 2, \dots, K \end{aligned} \quad (4)$$

In Function (3), $ETE(y_{k'}^t, x_{k'}^t, b_{k'}^t; y_{k'}^t, -b_{k'}^t)$ is a function of environmental technology efficiency. The difference between environmental technology efficiency and traditional technology efficiency lies in the difference between output frontiers. The directional environmental output distance function simultaneously considers the maximum possible reduction in undesirable goods given the expansion of desirable output [37]. If the observation point is on the environmental production frontier, then the value of directional distance function is 0, and the environmental technology efficiency is 1. Greater environmental technology efficiency indicates that the observation point is closer to the environmental

production frontier. This implies that given a fixed amount of input, the gap between the actual output and the maximum desirable output and the gap between the actual undesirable output and minimum undesirable output are both small [38]. We adopt the environmental technology efficiency to measure the water utilization efficiency of China's inter-provincial water resources.

3.2. Spatial Correlation Coefficient

Water utilization efficiency has two spatial effects: spatial correlation and spatial heterogeneity. Spatial correlation measures the overflow and diffusion effect of utilization efficiency between neighboring provinces. Spatial heterogeneity refers to the spatial differences of the utilization efficiency between the urban resources centers and the rural areas, which leads to the inter-provincial differences of utilization efficiency. Both aspects of spatial effect are measured by the spatial auto-correlation coefficient Global index Moran's I [39,40]. Global Moran's I is defined as:

$$\text{Moran's I} = \frac{n}{\sum_{i=1}^n (x_i - \bar{x})^2} \frac{\sum_{i=1}^n \sum_{j=1}^n W_{ij} (x_i - \bar{x}) (x_j - \bar{x})}{\sum_{i=1}^n \sum_{j=1}^n W_{ij}} \quad (5)$$

Here, W_{ij} is a spatial weight matrix, n is the number of spatial units, x_i and x_j are the variables' observed value of areas i and j , respectively. \bar{x} is the average value of observed value x . Generally the value of global Moran's I is between -1 and 1 . A value of 1 indicates the measured variables are perfectly positively correlated. A value of -1 suggests the variables are perfectly negatively correlated. A value of 0 indicates the measured variables are not spatially correlated. To test whether the value of Moran's I is significant, we use the following test formula:

$$z = \frac{[I - E(I)]}{\sqrt{\text{VAR}(I)}} \quad (6)$$

3.3. Spatial Panel Data Models: the Spatial Auto-Correlation Model (SAR) and the Spatial Error Model (SEM)

When using the ordinary least square method to estimate parameters in Equation (6), the spatial correlation of residual errors is ignored. The resulting parameter estimates are biased. Spatial models can resolve such problems resulting from spatial dependence and spatial correlation among variables. Classic spatial econometric models include spatial auto-regressive model (SAR) and spatial error model (SEM) [41].

The spatial auto-regressive model (SAR) is defined as:

$$\begin{cases} y = \rho W_1 y + X\beta + \mu \\ u = \lambda W_2 + \varepsilon \\ \varepsilon \approx N(0, \sigma_\varepsilon^2 I_n) \end{cases} \quad (7)$$

where y is the dependent variable; ρ and λ are spatial auto-regressive parameters measuring the spatial dependence of dependent variables; W is spatial weight matrix of $n \times n$ dimensions where 0 and 1 spatial-adjacency matrixes are commonly used; and ε is the random error term.

Spatial error model (SEM) [42] is:

$$\begin{cases} y = X\beta + \varepsilon \\ u = \lambda W_1 \varepsilon + \mu \\ \varepsilon \approx N(0, \sigma_\varepsilon^2 I_n) \end{cases} \quad (8)$$

where β is the regression coefficient measuring the impact of the explanatory variables X on the dependent variable y ; μ is the normally distributed random error term; and λ is the spatial error

coefficient, an $n \times 1$ vector measuring the spatial correlation of variables' residuals. The spatial correlation of the SEM model reflects the correlation between the spatial and random error terms.

If the utilization efficiency of inter-provincial water resources is influenced by spatial correlation, then not taking spatial correlation into account will cause OLS estimates to be biased. Therefore, this paper adopts the spatial panel data model to analyze factors affecting water utilization efficiency for the thirty provinces in China. We first decide between a fixed effect model and a random effect model. The fixed effect model shows individual provinces can affect the regression variables while the random effect model ignores any provincial effects. We use the fixed effect model since we intend to study the individual effects of the provinces. Based on Equations (7) and (8), the spatial correlation panel data model with fixed effect is defined as follows:

$$WUE_{i,t} = \alpha_i + \beta_1 EG_{i,t} + \beta_2 IS_{i,t} + \beta_3 TP_{i,t} + \beta_4 GI_{i,t} + \beta_5 EO_{i,t} + \beta_6 WE_{i,t} + \beta_7 WP_{i,t} + \delta \sum_j W_{ij}(WUE_{i,t}) + \mu_{i,t} \quad (9)$$

$$u_{i,t} = \lambda \sum_j \sum_{ij} u_{i,t} + \varepsilon_{i,t} \quad (10)$$

In Equation (9), WUE represents water utilization efficiency, δ represents spatial auto-regressive coefficient, and λ represents spatial error auto-correlation coefficient. If the value of δ is 0, then the model is a spatial error model (SEM). If the value of λ is 0, then the model is a spatial autoregressive model (SAR). α_i represents the fixed effect. For the other variable definitions, see Table 1. We examine the factors influencing utilization efficiency of China's inter-provincial water resources using Equations (9) and (10).

Table 1. Description of variables influencing water utilization efficiency.

Variable Name	Variable Definition	Units	Date Sources
Economic Growth (EG)	Ln (real GDP per capita)	Yuan/Person	<i>China Statistical Yearbook , Compilation of Statistics of 60 Years in New China, China Water Resources Bulletin [43–45].</i>
Industrial Structure (IS)	value-added of the primary industry/total GDP	%	
Technological Progress (TP)	R and D value/total GDP	%	
Government Influence (GI)	agricultural and forestry water expenditure/general budget expenditure	%	
Economic Openness (EO)	total volume of imports and exports/total GDP	%	
Water Endowment (WE)	Ln (water resources per capita)	m ³ /Person	
Water Price (WP)	Annual household expenditure on water/annual household total consumption expenditure	%	

3.4. Data

3.4.1. Data for Directional Distance Function

For input factors, we collected data on capital stock, labor, and water resources for China's thirty provinces (Chongqing and Sichuan are combined) from 1999 to 2014. For output, provincial GDP and sewage discharges were used. Variables are described as below:

- (1) GDP. The provincial annual GDP variable is the real GDP calculated at the fixed prices of 1995. Data is from *China Statistical Yearbook* and *Compilation of Statistics of 60 Years in New China* [43,44].
- (2) Sewage discharges. There are several methods of processing undesirable output: the negative output method, the linear conversion method, and the nonlinear conversion method. Of these three, the linear conversion method maintains the convexity and linear relationship because it is based on the classification invariance principle of the BCC model, commonly used by the

- DEA (Seiford [16]). Therefore, we adopt the linear data conversion method to convert sewage discharges data. We use a linear data conversion function, $f(b) = v - b$, to convert sewage discharges into output. Specifically, v is a large enough vector which ensures all converted desirable output is positive, b is the total amount of each province's industrial and domestic wastewater discharges. Wastewater data is from various years of the *China Statistical Yearbook* [43].
- (3) Capital stock. Researchers generally use the “perpetual inventory method” to estimate the capital stock. The capital stock is estimated by: $K_{i,t} = I_{i,t} + (1 - \delta_{i,t})K_{i,t-1}$, where $K_{i,t}$ is the capital stock of region i in year t ; $I_{i,t}$ is the investment of region i in year t , and $\delta_{i,t}$ is the capital depreciation rate for region i in year t . We use the China's estimated national and provincial capital stock data for the period from 1999 to 2006 in Shan [46]. The real capital stock data at the 1995 dollar after 2006 is calculated using the perpetual inventory method.
 - (4) Labor. The provincial labor force is calculated as the average rate of employment at the end of the year and employment at the end of previous corresponding year. Because the average education level of each province is not available, differences in labor quality are not included. Employment data is from various years' *China Statistical Yearbook* [43].
 - (5) Water resources. Provincial water consumption is used as the water resource input. This is aggregated from industrial, agricultural, ecological water, and household water supplies. Data is collected from various years of the *China Statistical Yearbook* [43] and the *China Water Resources Bulletin* [45].

3.4.2. Variables Influencing Utilization Efficiency of Inter-Provincial Water Resources

The improvement of water utilization efficiency is essential to sustainable economic growth and development. Studying factors influencing the utilization efficiency of water resources can directly contribute to sustainable economic development in China's various regions. Factors commonly considered to affect water utilization efficiency include economic growth, industrial structure, technological progress, market-oriented reform, economic openness, and the price of the water resource. The faster the economy grows, the greater the possible improvement of water utilization efficiency and allocative efficiency [47]. The difference in water consumption intensity by industries makes industrial structure important to water utilization efficiency. As industrial structure shifts from low-productivity sectors to high-productivity sectors/industries, water utilization efficiency of the whole country can improve [48,49]. This is normally referred to as the “Structural-Dividend Hypothesis”. Technological progress brings forth new and improved technology and new equipment; which in turn generally improves production efficiency and can reduce water consumption in the production process [50]. Economic openness brings advanced technology, equipment, and management through human capital enhancements and technology diffusion. It also strengthens local industries through competition and positive spillover-effect. This leads to improvements in water utilization efficiency. Barbier [51] shows that increasing economic openness not only helps to optimize resource allocation and reduce resource waste but also promotes new resource-conserving technologies and innovations. Markets regulate people's economic behaviors through price signals and relying on competitive pricing to improve allocative efficiency of resources, including water resources [52,53]. If an increase in the price of water means a reduction of a firm's profits by increasing production costs, industries will try to improve the efficiency of water utilization. Ma [14] finds that water price increases can promote people to utilize water resources more efficiently. He further notes that current water price formulation neglect serological maintenance costs and the environmental impacts of large-scale water projects. The “resource curse” hypothesis holds that a region with low opportunity cost of using resources tends to distort resource allocation through overuse when planning industrial structure and production, thereby reducing the utilization efficiency significantly. Our study does find that regions endowed with abundant water resources in China have relatively low utilization efficiency while regions with limited water resources have higher utilization efficiency; this is consistent with findings by Wang [54].

This paper examines the impact on utilization efficiency of the following variables: economic growth (EG), industrial structure (IS), technological progress (TP), economic openness (EO), water resources endowment (WE), water resources price (WP), and government influence (GI). The descriptions of the variables are listed in Table 1.

4. Results and Discussion

4.1. Analysis of the Inter-Provincial and Regional Differences in Water Utilization Efficiency

Using the directional distance function with environmental considerations in Equation (3), we estimate the water utilization efficiency of China's thirty provinces for the period from 1999 to 2014. Table 2 shows great regional variation in water utilization efficiency. The average water utilization efficiency in Tianjin, Shanghai, and Yunnan are at the production frontier while the utilization efficiency of the rest of the provinces are away from the production frontier. The most efficient provinces are Tianjin, Shanghai, Yunnan, Beijing, and Qinghai. The bottom five provinces in utilization efficiency are Xinjiang, Inner Mongolia, Gansu, Hubei, and Ningxia. Provinces with high utilization efficiency are mainly located in China's eastern coastal region, and provinces with low utilization efficiency are mainly distributed inland. Yunnan province, however, which is located in China's western inland region, has been at the utilization efficiency frontier in recent years. It is mainly due to Yunnan's agriculture-based economy and the low industrialization level.

Table 2. Water utilization efficiency in China.

Year	1999	2001	2003	2005	2007	2009	2011	2013	Average
Beijing	0.994	0.976	0.978	0.899	1.000	1.000	1.000	1.000	0.985
Tianjin	1.000	0.998	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Hebei	0.576	0.562	0.554	0.537	0.527	0.516	0.532	0.511	0.542
Shanxi	0.786	0.706	0.754	0.733	0.742	0.735	0.756	0.743	0.748
Inner Mongolia	0.274	0.325	0.259	0.276	0.261	0.202	0.213	0.203	0.248
Liaoning	0.873	0.876	0.889	0.901	0.903	0.913	0.926	0.937	0.902
Jilin	0.577	0.502	0.513	0.487	0.489	0.506	0.512	0.505	0.514
Heilongjiang	0.378	0.382	0.288	0.434	0.456	0.479	0.468	0.477	0.426
Shanghai	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Jiangsu	0.489	0.417	0.435	0.420	0.439	0.468	0.539	0.556	0.471
Zhejiang	0.718	0.692	0.664	0.624	0.611	0.621	0.612	0.624	0.645
Anhui	0.695	0.700	0.688	0.659	0.632	0.584	0.599	0.604	0.649
Fujian	0.629	0.596	0.527	0.532	0.543	0.512	0.508	0.521	0.551
Jiangxi	0.543	0.515	0.523	0.534	0.587	0.554	0.565	0.623	0.561
Shandong	0.714	0.715	0.699	0.678	0.688	0.662	0.669	0.645	0.688
Henan	0.588	0.592	0.577	0.556	0.579	0.533	0.547	0.516	0.563
Hubei	0.414	0.336	0.378	0.355	0.378	0.362	0.357	0.379	0.376
Hunan	0.452	0.399	0.435	0.487	0.498	0.477	0.457	0.487	0.469
Guangdong	0.498	0.484	0.465	0.477	0.488	0.474	0.472	0.497	0.487
Guangxi	0.349	0.336	0.357	0.487	0.468	0.456	0.445	0.476	0.448
Hainan	0.727	0.881	0.906	0.926	0.981	0.973	0.927	0.931	0.913
Sichuan	0.655	0.616	0.594	0.585	0.572	0.567	0.559	0.567	0.562
Guizhou	0.512	0.528	0.495	0.496	0.526	0.475	0.469	0.488	0.506
Yunnan	1.000	0.998	1.000	0.996	1.000	1.000	1.000	1.000	1.000
Tibet	0.772	0.734	0.803	0.834	0.902	0.913	0.924	0.931	0.852
Shaanxi	0.479	0.507	0.523	0.576	0.566	0.542	0.498	0.548	0.554
Gansu	0.332	0.312	0.342	0.346	0.359	0.344	0.352	0.366	0.351
Qinghai	0.744	0.957	0.948	1.000	0.894	0.898	1.000	1.000	0.93
Ningxia	0.372	0.378	0.388	0.423	0.431	0.402	0.369	0.488	0.418
Xinjiang	0.076	0.074	0.087	0.110	0.098	0.087	0.095	0.116	0.011
East China	0.779	0.745	0.738	0.727	0.744	0.740	0.744	0.747	0.744
Central China	0.579	0.517	0.520	0.518	0.533	0.504	0.508	0.517	0.525
West China	0.506	0.524	0.527	0.557	0.552	0.535	0.539	0.562	0.535
Total	0.616	0.603	0.602	0.609	0.617	0.602	0.606	0.618	0.609

Note: Due to limitation of space, only values of utilization efficiency for the odd-numbered years are listed.

Table 2 also demonstrates the significant differences in water utilization among the major regions in China: eastern, western (East China includes Beijing, Tianjin, Hebei, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong, Hainan, Liaoning; Central China includes Shanxi, Jilin, Heilongjiang, Anhui, Jiangxi, Henan, Hubei, Hunan; West China includes Inner Mongolia, Guangxi, Sichuan (including Chongqing), Guizhou, Yunnan, Tibet, Shaanxi, Gansu, Qinghai, Ningxia, Xinjiang.), and central. The utilization efficiency in China's eastern region is far better than the other two regions. Its value fluctuates around 0.744. The utilization efficiency in the western region varies around 0.535 and for the central region, which is relatively underdeveloped, its utilization efficiency oscillates around 0.525. For the 16-year sample period, the water utilization efficiency of the central and western regions are always below the national average while that of the eastern region is always above. The economy of the eastern region is well-developed, more market-oriented, and can quickly adjust to industrial structural changes. As a result, the eastern region uses its water resources more efficiently than other regions. Our results also show higher water utilization efficiency for the western region compared to the central region. This contradicts other studies [44]. This result is mainly because we include the undesirable output, such as environmental pollution, in our production function. In addition, the western region has a more beneficial industrial structure and better ecological protection than those in the central region.

4.2. Spatial Correlation Analysis of Regional Water Utilization Efficiency

Based on Equations (5) and (6), we compute the Global Moran's I index of China's inter-provincial water utilization efficiency using software. Table 3 shows the Global Moran's I index. All values are positive and significant at the 1% level. These results mean that the changes in water utilization efficiency in China are characterized by positive spatial correlation. The pattern of spatial distribution shows strong spatial aggregation rather than random distribution. That is, regions that have similar water utilization efficiencies have strong spatial aggregation characteristics.

Table 3. Moran's I index of water utilization efficiency in China.

Year	Moran's I	Z(I)	p	Year	Moran's I	Z(I)	p
1999	0.0673	2.8988	0.0000	2007	0.0712	3.0251	0.0002
2000	0.0677	2.9211	0.0001	2008	0.0736	3.0986	0.0001
2001	0.0732	3.0899	0.0000	2009	0.0823	3.2973	0.0000
2002	0.0623	2.7466	0.0001	2010	0.0845	3.3216	0.0000
2003	0.0645	2.7588	0.0000	2011	0.0773	3.1084	0.0000
2004	0.0652	2.8581	0.0000	2012	0.0992	3.7238	0.0000
2005	0.0661	2.8784	0.0000	2013	0.1052	3.8807	0.0000
2006	0.0659	2.8702	0.0000	2014	0.1068	3.9211	0.0001

4.3. Analysis of Factors Influencing Water Utilization Efficiency

4.3.1. Selection of Spatial Panel Data Models

We estimated Equation (9) using the software to test whether the spatial correlation of model's residual error term is significant. Table 4 presents the goodness-of-fit test values of the mixed model, the spatial fixed effect model, the time fixed effect model, and the two-way fixed effect model. The R-square for the mixed model is 0.5812 and it rises to 0.6339 after adding the spatial fixed effects. It further rises to 0.8914 when both the spatial fixed effect and time fixed effect are included in the model. The values of log-likelihood function for the four models are 260.92, 536.44, 276.06, and 738.78, respectively. Based on R-square, the log-likelihood function and the DW value, the two-way fixed effect model has the best goodness-of-fit statistics. Therefore, we adopted the two-way fixed effect model to analyze factors influencing utilization efficiency of China's inter-provincial water resources.

Table 4. Estimation and different types panel data models.

Variable	Mixture	Spatial Fixed Effects	Time Fixed Effects	Two-Way Fixed Effects
Economic Growth (EG)	0.0362 *** (2.7375)	0.1301 ** (2.0639)	0.0916 *** (3.5218)	0.2058 *** (2.6472)
Industrial Structure (IS)	−0.0657 *** (5.0422)	−0.0539 ** (2.3118)	−0.0327 *** (2.7278)	−0.1112 *** (3.3104)
Technological Progress (TP)	0.2173 * (1.8718)	0.1266 ** (2.2801)	0.2574 ** (2.3176)	0.1489 *** (2.6129)
Government Influence (GI)	−0.0028 ** (−2.0298)	−0.0175 ** (−2.1106)	−0.0077 *** (−2.8967)	−0.0198 *** (−2.8847)
Economic Openness (EO)	0.0634 *** (2.7662)	0.1152 *** (2.8139)	0.1074 *** (2.6458)	0.1413 *** (3.0536)
Water Endowment (WE)	−0.1015 ** (−2.0093)	−0.1206 *** (−2.8677)	−0.1153 ** (−2.1248)	−0.1056 ** (2.1142)
Water Price (WP)	−0.0085 (−1.0109)	0.1076 (0.9692)	0.0133 * (1.7244)	−0.1109 (1.1536)
R-squared	0.5812	0.6339	0.6192	0.8914
Log-Likelihood	260.9263	536.4437	276.0603	738.7802
D.W.	2.0031	1.7614	1.5968	2.1043
LM-lag	2.1536 *	30.3249 ***	3.9876 *	15.6729 **
Robust LM-lag	18.4276 ***	2.5672 *	26.7633 ***	0.3203
LM-err	12.3628 **	28.1371 ***	16.6047 ***	18.1928 ***
Robust LM-err	28.6368***	0.3794	39.3894 ***	2.8402 **

Note: *** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$.

Table 4 also provides Lagrange Multiplier statistics (LM) for us to choose between the spatial auto-regressive (SAR) model and spatial error-correction (SEM) model. The LM statistics for the auto-regressive two-way fixed effect model (LM-lag) is 15.67 (significant at 5% level), and the LM test for error-correction model (LM-err) is 18.19 (significant at 1% level). Both statistics indicate the spatial correlation in residuals for the two-way fixed effect model. We next report results of both SAR and SEM models.

4.3.2. Results of Spatial Panel Data Models

The results of the spatial auto-regressive model (SAR) and spatial error model (SEM) are shown in Table 5. We added a lagged dependent variable term to the SAR model, $W^* \text{ dep. Var.}$ and for the SEM model, a spatial error term, spat. error , is added. The coefficients of both added variables are significant at 1%. The R-Square values are 0.9012 and 0.9244, respectively. The signs of the estimated coefficients of the spatial panel data models are consistent with those of the regular panel model. However, the values of the t -test improve for the two spatial models. In the two-way fixed effect spatial model, the log-likelihood value of the SEM model is higher than that of the SAR model, which indicates the slightly better explanatory power of the SEM model. This is consistent with the results of the goodness-of-fit tests in Table 4. We discuss the results of spatial error model (SEM) next.

Economic growth is significantly and positively correlated with water utilization efficiency. Holding other things constant, a one-unit increase in $\ln(\text{real GDP per capita})$ leads to an increase of 0.23 units in national water utilization efficiency. Regions with higher economic growth and higher local industrial cluster tend to benefit from economies of scale in water utilization [55]. Moreover, high economic growth leads to increasing local government budgets, which in turn helps with funding infrastructure for improving water resources and the prevention and treatment of water pollution.

Our measure of industrial structure has a negative effect on water utilization efficiency. The bigger are the proportion of agriculture, forestry, animal husbandry and fishery in the economy; the lower is the region's utilization efficiency. The technology of using agricultural water is not well

advanced in China. Most regions still adopt water-intensive irrigation methods, such as: string irrigation, flood irrigation, and large-scale irrigation. Only about 2.6% of the total irrigated areas adopt water-conserving irrigation methods such as sprinkler irrigation and micro irrigation. Only about one third of the total irrigation water goes to crops production [56]. Thus, areas with heavy agricultural water consumption have lower utilization efficiency.

Table 5. Estimation of the two-way fixed effects spatial econometric model.

Variable	SAR	SEM
Economic Growth (EG)	0.2162 *** (3.1317)	0.2319 *** (3.4363)
Industrial Structure (IS)	−0.1215 *** (4.0462)	−0.0893 *** (5.1361)
Technological Progress (TP)	0.1673 *** (2.8971)	0.1716 *** (3.1285)
Government Influence (GI)	−0.0162 *** (−3.0219)	−0.0205 *** (−3.8826)
Economic Openness (EO)	0.1263 *** (3.7166)	0.1425 *** (4.4172)
Water Endowment (WE)	−0.0981 ** (−2.1409)	−0.1107 *** (−2.8767)
Water Price (WP)	−0.0908 (−1.2109)	−0.1627 (−1.4019)
W* dep. var	0.2748 *** (4.2186)	
Spat error		0.3174 *** (5.9178)
R-squared	0.9012	0.9244
Log-L	741.5254	748.8528

Note: *** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$.

Technological progress contributes to the utilization efficiency of inter-provincial water. Technological progress improves the efficiency of production equipment including reductions in water utilization and sewage discharge during production processes. Moreover, technological advancement improves the quality of labor force, implying it indirectly reduces the water waste and raises water utilization efficiency [57]. In China, utilization efficiency of industrial water has improved dramatically in recent years due to the upgrading of industrial production equipment. Water utilization efficiency is significantly lower in the central and western regions because of the advanced science and technology and higher foreign capital investment available in the eastern coastal region.

As expected, government influence, as measured by agricultural and fishery share of government spending, has a negative impact on water utilization efficiency. The size of the impact is relatively small. One unit increase in government influence reduces 0.0205 units of efficiency of China's water resources. However, government influence has different effects in different regions. For the nation as a whole and for the eastern region, more governmental expenditure on agriculture and forestry lowers the utilization efficiency. For the western region, government expenditure can significantly improve the utilization efficiency. Because of the intensive agricultural water utilization in the western region, the government can guide the farmers to adopt water-conserving irrigation methods by constructing agricultural water infrastructure. This in turn improves water utilization efficiency.

Economic openness brings new technology, advanced equipment, and state-of-the-art management strategies, thereby improving regional utilization efficiency as well as reducing wastewater discharge [58]. The "green trade policy" promoted by developed countries has

forced developing countries to adopt new technologies and equipment and to implement environmental-friendly production processes, including the reduction of water consumption.

The “Resource Curse Theory” states that the utilization efficiency is lower in regions with rich resource endowments. Our results are consistent with this theory. There are large disparities in water endowment between different regions in China that lead to great differences in utilization efficiency. For instance, the per-person water resource of Beijing city is less than 200 cubic meters. That is approximately one-twentieth of the national average and one-eightieth of the world’s average. Not surprisingly, Beijing’s water utilization efficiency is relatively high (above 0.95). Conversely, a province with rich water resources, has low utilization efficiency (only 0.471 on average). The main reason for the relative low efficiency is the concentration of water-intensive industries, in particular, chemical and garment industries in this province.

The price of water resources does not seem to play a role on utilization efficiency. Therefore, it may be difficult to discourage water consumption or alleviate water pollution through alternative pricing strategies. In fact, the current pricing of water in China basically adopts “single determinant” water pricing. That is, when determining the water price, the government is more concerned about people’s ability to pay rather than the production costs or the cost of pollution treatment. Alternatively, the government should price water to reflect the environmental impacts of water supply projects, damage-compensating costs, resources protection costs, and resource recovery costs. Since income per-capita in China is relatively low, such pricing strategies are likely more of a longer-term water utilization improvement program.

5. Conclusions

Improvement of water utilization efficiency is crucial to sustainable economic growth and social development. Using the directional distance function with environmental considerations, we estimate the utilization efficiency of China’s inter-provincial water resources for the period from 1999 to 2014. The estimated utilization efficiency takes the environmental degradation and the undesirable output into account in the analysis. Our research also analyzes the regional differences and spatial correlation of the environmental efficiency of China’s water utilization. Furthermore, we examine the factors influencing water utilization efficiency by applying spatial panel data models. We find that provinces with high environmental utilization efficiencies are mainly located in economically-developed coastal regions in China while inland provinces have low water utilization efficiency. The Moran’s I index of utilization efficiency indicates a significant spatial auto-correlation and spatial heterogeneity in China’s water utilization efficiency. Moreover, our results show that economic growth, technological progress, and economic openness promote the environmental utilization efficiency of water resources. Industrial structure, government influence, and water endowment negatively impact water utilization efficiency. The price of water does not play a role in water utilization efficiency currently, likely because it is not a market price.

Water shortage and water pollution have become environmental obstacles for China’s sustainable development. It is essential to direct China’s rapid economic growth onto a sustainable path by improving its water utilization efficiency. The government should improve economic openness to promote importation of foreign advanced water-conserving technologies and management. In addition, the government could help water utilization efficiency by encouraging technological progress in transforming China’s industrial structure, specifically transforming water-intensive industries into low-water-consuming industries. Furthermore, strengthening economic and technical exchanges across regions/provinces, overcoming regional/provincial trade protectionism, and accelerating the technology diffusion from developed regions/provinces to the developing regions/provinces are also policies that could improve water utilization efficiency and promote sustainable growth.

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Abbreviations

The following abbreviations are used in this manuscript:

DEA	Data envelopment analysis
C-D	Cobb-Douglas
SAR	Spatial auto-regressive model
SEM	Spatial error model
LM	Lagrange multiplier

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