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Evaluation of Water Use Efficiency of 31 Provinces and Municipalities in China Using Multi-Level Entropy Weight Method Synthesized Indexes and Data Envelopment Analysis

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Abstract: China's water shortage problem is becoming increasingly severe. Improving water use efficiency is crucial to alleviating China's water crisis. This paper evaluates the water use efficiency of 31 provinces and municipalities in China by using the data envelopment analysis (DEA) method. When the usual DEA model has too many indexes selected, it will cause the majority of the decision making units (DMUs) efficiency values be one, which leads to invalid evaluation results. Therefore, by using the entropy weight method, a new synthetic set of indexes is constructed based on the original indexes. The new synthetic set of indexes retains the full information of the original indexes, and the goal of simplifying the number of indexes is achieved. Simultaneously, by empowering the original indexes, the evaluation using synthetic indexes can also avoid the impact of industrial structure and labor division on water use efficiency. The results show that in China's northeastern grain producing areas, water use efficiency is higher due to the high level of agricultural modernization. The provinces in the middle reaches of the Yangtze River have the lowest water use efficiency due to water pollution and water waste. In general, China's overall water use efficiency is low, and there is still much room for improvement.

Keywords: DEA; entropy weight method; evaluation indexes; water use efficiency

1. Introduction

With the impacts of climate change, China has become a country which frequently suffers from drought and severe water shortages. But as the world's most populous country, and the second largest economy in the world, China consumes the largest amount of water [1–3]. In 2017, China's total water consumption was 604.34 billion cubic meters, and the per capita water consumption was 435.91 cubic meters. According to research conducted by the United States Geological Survey, the total water consumption in the US in 2015 was 445.3 billion cubic meters, and the per capita water consumption was 1387.23 cubic meters [4–6]. The US water consumption in 2015 reached the lowest since 1970, and it continued to decline due to the improvement in water use efficiency. On the contrary, China has a vast territory and a large population [7–9]. The distribution of water resources across China is uneven, and regions are at different developmental stages. With the growth of China's economy and the increase in the use of water for living and industrial purposes, the contradiction between China's water supply and demand will be further exacerbated [10–13]. Therefore, the analysis and evaluation of water use efficiency in 31 provinces and municipalities in China are crucial for understanding the current water shortage problem and therefore, the improvement of water use efficiency in China [14,15].

The existing literature provided various methods to evaluate the efficiency of water use. The most common method is to use the water consumption per unit of output value as an index to analyze the regional difference in water use efficiency. However, such an index cannot comprehend the impacts of various factors on water use efficiency. Therefore, the water consumption per unit of output value, which measures some social and industrial influences, is used instead as an index in a more comprehensive evaluation index system. The evaluation index system method is an effective method for evaluating the efficiency of water use [16,17]. By selecting appropriate water consumption and socioeconomic data as indexes, and then determining the weight for each index, it is possible to score the water use efficiency in each region. However, the index evaluation method can only calculate the comprehensive score of each index based on the weight, it cannot evaluate the water use efficiency from the perspective of input-output efficiency analysis. Water is an important resource for living and industrial activities. Therefore, a proper evaluation of water use efficiency should comprehend the input-output efficiency of human activities. As an alternative, the data envelopment analysis (DEA) method based on input-output theory is more suitable for the evaluation of water use efficiency [18,19].

The water resource system is a complex and large system, and it may be affected by multiple factors. When using the DEA model to evaluate the water use efficiency, often many indexes must be included, and the meanings between the indexes are significantly different. However, when the number of selected indexes is too large, relative to the number of decision making units (DMUs), the results will often indicate that most of the DMUs are effective in their actions, causing the evaluation results to be invalid. Excessively dispersed index meanings can cause the model results to fail to catch the essence of the main problem [20,21]. In order to solve such a problem, this paper proposes an improved DEA model based on the multi-level entropy weight method, and applies this model to analyze the water use efficiency of 31 provinces and municipalities in China in 2017.

2. Method

In general, using the DEA model, the indexes are grouped into two categories, namely, input indexes and output indexes. The index's value is substituted into the DEA model to calculate the relative efficiency of each DMU. The method utilized in this paper synthesizes a new set of indexes based on the original indexes. This method essentially replaces the original indexes with the new synthetic indexes and applies them in the DEA model. Through such modification, the problem that too many input indexes are relative to the DMUs can be resolved, and the synthetic indexes have more prominent and clear meanings [22,23].

2.1. Selection and Synthesis of Indexes

In order to evaluate the water use efficiency of 31 provinces and municipalities in China, this paper selects 23 original indexes and divides them into 6 categories according to their actual meanings. All rare data are collected from the China Statistical Yearbook 2017. These 6 categories are defined as new synthetic indexes. The specifications and meanings are shown in Table 1.

In selecting the input and output indexes for the DEA model, the inputs of DMU, which include the corresponding indexes that have a negative impact on the overall system, are taken as the input indicators. Conversely, the outputs of DMU, which can exert a positive effect on the system, are used as output indicators. In particular, we regard the integrated water pollution load as the input index of the DEA model, and the water endowment as the output indicator. According to Table 1, we then calculate the values of each synthetic index and the weighted average of the original indicators included in each synthetic index [24]. In order to avoid the influence of subjective empowerment on the results and to retain the information contained in the original indicators as much as possible, this paper uses the entropy weight method to calculate the weights.

Table 1. Synthesis indexes and meaning.

	Synthetic Index	Index Meaning	Original Index
Input Index	Water conservancy investment	Indicates the combined input of DMUs in water supply facilities	Water supply pipe length Water conservancy fixed asset investment
	Comprehensive water consumption	Indicates the intensity of integrated water use in DMUs	Agricultural water consumption Industrial water consumption Domestic water consumption Ecological water consumption Per capita water
	Integrated water pollution load	Indicates the level of integrated pollutant emissions from DMUs	Total wastewater discharge Chemical oxygen demand (COD) Ammonia nitrogen Total nitrogen Total phosphorus
Output Index	Water endowment	Indicates the level of natural water resources in DMUs	Surface water resources Groundwater resources Per capita water resources
	Comprehensive economic output	Responds to the overall economic output of each DMU	Primary industry output value Secondary industry output value Tertiary industry output value Per capita GDP Number of employed people
	Integrated crop yield	Responds to the overall crop yield level of each DMU	Effective irrigated area Grain production Per capita grain production

2.2. Multi-Level Entropy Weight Method

The entropy weight method is an objective weighting method that can be used in any process that requires the determination of the weight. In addition, it can be combined with some other methods. The entropy weight method uses the rare data of the indicators to obtain the entropy weight of each index according to the degree of dispersion of the data. It then utilizes the entropy weight to align each index, and then calculates the weight of each index. Compared with the subjective weighting method, the entropy weight method has high objectivity and can reasonably explain the final result [25–27]. In addition, compared with other objective weighting methods, the entropy weight method has no complicated linear relationship, which is simpler and has a wider scope of application. In the general entropy weight method evaluation, all the indexes are used at the same level for weight calculation. In order to combine the idea of input-output analysis in a DEA model, this paper constructs a multi-level entropy method. According to the classification of indexes proposed above, this method calculates weights for each category of indexes by entropy weight method and ensures that the sum of the weight values for each category of indexes is 1. Based on the weight score of each category of indexes, the corresponding synthetic indexes are then calculated, and the values are used as the new input-output data instead of the original indexes to be substituted into the DEA model for efficiency evaluation [28,29].

The calculation process of the entropy weight method is as follows:

(1) Standardizing each evaluation index for data comparison.

Positive impact indicators:

$$r_{ij} = \frac{x_{ij} - x_{i\min}}{x_{i\max} - x_{i\min}} \tag{1}$$

negative impact indicators:

$$r_{ij} = \frac{x_{i\max} - x_{ij}}{x_{i\max} - x_{i\min}} \tag{2}$$

where: r_{ij} is the normalized value of the j-th evaluation index of the i-th evaluation object; x_{ij} is the original value of the j-th evaluation index of the i-th evaluation object before standardization; $x_{i\min}$ and $x_{i\max}$ are the minimal and the maximal value of the i-th index, respectively [30].

(2) Building the decision matrix:

$$R = (r_{ij})_{m\times n} \tag{3}$$

where there are m number of evaluation object and n number of evaluation indicators.

(3) Calculating the index entropy value H_i:

$$H_i = \frac{-1}{\log_e n}\sum_{j=1}^{n} f_{ij}\log_e f_{ij} \tag{4}$$

$$f_{ij} = \frac{r_{ij}}{\sum\limits_{j=1}^{n} r_{ij}} \tag{5}$$

where: $i = 1, 2, \ldots, \mathrm{m}$, when $f_{ij} = 0$, $f_{ij}\log_e f_{ij} = 0$.

(4) Calculating the indicator weight value W_j:

$$W_j = \frac{1 - H_j}{n - \sum\limits_{j=1}^{n} H_j} \tag{6}$$

(5) Comprehensive evaluation value WVI.

Calculating water vulnerability using linear weighting method:

$$WVI = RW_j = \sum_{i=1}^{m} X_{ij}W_j \tag{7}$$

2.3. DEA Method

Data envelopment analysis is a multi-factor productivity efficiency evaluation method, which was firstly proposed by Charnes A, Cooper W, and Rhodes E in 1978. The principle of this method is to treat each object of evaluation as a DMU, keep the output or input of DMU unchanged, and determine the relatively effective production frontier, and then project each DMU onto the production frontier. Their relative efficiency is evaluated by comparing the deviation from the DEA production frontier [31–34].

DEA has a variety of measurement models, including CCR, BCC, ST, FG, etc. Suppose there are n number of DMUs in a system, each of them has m number of input indicators ($\mathrm{x_{m1}}$,$\mathrm{x_{m2}}$, … ,$\mathrm{x_{mj}}$) and s number of output indicators ($\mathrm{y_{s1}}$,$\mathrm{y_{s2}}$, … $\mathrm{y_{sj}}$). Then the DEA model is:

$$\text{s.t}\begin{cases} min\left[\theta - \varepsilon\left(e_1^T S^+ + e_2^T S^-\right)\right] \\ \sum\limits_{j=1}^{n} \lambda_j X_j + S^- - \theta X_{j0} = 0 \\ \sum\limits_{j=1}^{n} \lambda_j Y_j - S^+ - Y_{j0} = 0 \\ \lambda_j \geq 0, (j = 1, 2, \ldots, \mathrm{n}) \\ S^+ \geq 0 \\ S^- \geq 0 \\ 0 \leq \theta \leq 1 \end{cases} \tag{8}$$

where, θ is the effective value; ε is the non-Archimedean infinitesimal, S^+ is the slack variable of m input, S^- is the slack variable of s output; λ_j is the weight vector of input and output; n is the number of DMU; and $e_1^T = (1,1,\ldots,1)_{1\times m}$, $e_2^T = (1,1,\ldots,1)_{1\times s}$.

The economic meaning is:

(1) if $\theta = 1$, while $S^+ = S^- = 0$, then DEA is effective;

(2) if $\theta < 1$, then DEA is invalid; when $\sum_{j=1}^{n}\lambda_j = 0$, technical efficiency, otherwise technical inefficiency. Let $K = 1/(\theta\sum_{j=1}^{n}\lambda_j)$, then we have: K = 1 indicating scale efficiency; K < 1 indicating increasing returns to scale; and K > 1 indicating decreasing return to scale [35–37].

3. Model Calculation and Result Analysis

3.1. Weight Calculation Result

According to the 23 original indexes of 31 provinces and municipalities in China in 2017, the entropy weights are calculated. The weights of the indexes are shown in Table 2.

Table 2. Index weight.

	Synthetic Index	Index Meaning		Weight Value
Input Index	Water conservancy investment	Indicates the combined input of DMUs in water supply facilities	Water supply pipe length	0.48
			Water conservancy fixed asset investment	0.52
	Comprehensive water consumption	Indicates the intensity of integrated water use in DMUs	Agricultural water consumption	0.18
			Industrial water consumption	0.22
			Domestic water consumption	0.17
			Ecological water consumption	0.23
			Per capita water	0.2
	Integrated water pollution load	Indicates the level of integrated pollutant emissions from DMUs	Total wastewater discharge	0.2
			COD	0.2
			Ammonia nitrogen	0.2
			Total nitrogen	0.2
			Total phosphorus	0.2
Output Index	Water endowment	Indicates the level of natural water resources in DMUs	Surface water resources	0.33
			Groundwater resources	0.26
			Per capita water resources	0.41
	Comprehensive economic output	Responds to the overall economic output of each DMU	Primary industry output value	0.2
			Secondary industry output value	0.22
			Tertiary industry output value	0.19
			Per capita GDP	0.2
			Number of employed people	0.19
	Integrated crop yield	Respond to the overall crop yield level of each DMU	Effective irrigated area	0.36
			Grain production	0.36
			Per capita grain production	0.28

It can be seen in Table 2 that in the category of water conservancy investment, the weight values of pipeline length and fixed asset investment are 0.48 and 0.52. This shows that in the water conservancy investment of 31 provinces and municipalities, there exists significant gaps in the amount of investment. In the category of comprehensive water consumption, the ecological water consumption has the largest weight of 0.23, while the domestic water consumption has the lowest weight of 0.17. Such a result shows that the difference in domestic water consumption is relatively small across regions, and the difference in ecological water consumption is quite notable. Since China's current policy emphasizes the governance and restoration of ecological environment, the increase in the weight of ecological water consumption is reasonable and understood. The weight of agricultural water consumption is lower than that of industrial water consumption, which may result in higher scores of the water use efficiency in agricultural regions. The calculated weights can also reduce the impact of water use efficiency due to different industrial divisions of labor. The agricultural sector has the highest water consumption, but its output value is not as high as in the industrial sector. Not only is agriculture related to national security, but it is also the basis for the development of other industries. Therefore, it is not fair to provinces that are mainly agriculture based, to only consider the total water consumption and total GDP when evaluating the water use efficiency. In the category of integrated water pollution load, the weights of the indicators are the same, which means that the types of pollutants faced by the addressed regions are roughly the same. However, it must be noted that the emissions of pollutants are different in these regions [38,39]. It can be observed from the water endowment indexes that, on one hand, the distribution of groundwater resources in different provinces and municipalities in China is small, and on the other hand, the distribution of surface water is quite different. Meanwhile, the difference in the amount of water resources per capita is significant due to the difference in population distribution. The weight analysis of comprehensive economic output indexes shows that the difference in industrial output value is the largest, and it is the smallest in tertiary industry. Among the integrated crop yield indexes, it is reasonable to increase the weight of the first two items to benefit the scores of the agricultural regions.

3.2. Water Use Efficiency Evaluation Results

According to the weight calculation results in the previous section, the new synthetic index values obtained are shown in Table 3. The data are substituted into the DEA model, and the results of the water use efficiency evaluations of the 31 provinces and municipalities are shown in Table 4. To illustrate the advantage of the multi-level entropy weighted DEA model, this study also uses the original indexes and simplified indexes as input-output data to compare the results of the evaluation of the water use efficiency. The results are presented in Table 4. In addition, the definitions of these simplified indexes set are shown in Table 5.

Table 3. Synthetic index values.

DMU	Water Conservancy Investment	Comprehensive Water Consumption	Integrated Water Pollution Load	Water Endowment	Comprehensive Economic Output	Integrated Crop Yield
Beijing	0.339	0.224	0.158	0.103	0.400	0.100
Tianjin	0.223	0.149	0.171	0.100	0.321	0.129
Hebei	0.430	0.251	0.446	0.124	0.385	0.517
Shanxi	0.173	0.159	0.253	0.124	0.217	0.259
Inner Mongolia	0.329	0.385	0.195	0.152	0.278	0.521
Liaoning	0.213	0.218	0.321	0.125	0.311	0.322
Jilin	0.229	0.210	0.212	0.146	0.248	0.522
Heilongjiang	0.213	0.288	0.271	0.190	0.279	0.900
Shanghai	0.246	0.202	0.291	0.102	0.410	0.109
Jiangsu	0.762	0.490	0.714	0.138	0.791	0.485
Zhejiang	0.603	0.269	0.488	0.190	0.541	0.195
Anhui	0.412	0.321	0.414	0.180	0.340	0.542
Fujian	0.490	0.260	0.402	0.218	0.417	0.176
Jiangxi	0.320	0.266	0.416	0.270	0.281	0.333
Shandong	0.538	0.298	0.583	0.136	0.685	0.617
Henan	0.565	0.383	0.461	0.156	0.481	0.683
Hubei	0.547	0.305	0.484	0.232	0.443	0.400
Hunan	0.586	0.316	0.504	0.294	0.378	0.416
Guangdong	0.735	0.430	0.900	0.285	0.778	0.237
Guangxi	0.332	0.292	0.400	0.327	0.292	0.258
Hainan	0.124	0.147	0.141	0.148	0.173	0.127
Chongqing	0.383	0.165	0.292	0.162	0.297	0.207
Sichuan	0.555	0.303	0.585	0.358	0.429	0.416

Table 3. *Cont.*

DMU	Water Conservancy Investment	Comprehensive Water Consumption	Integrated Water Pollution Load	Water Endowment	Comprehensive Economic Output	Integrated Crop Yield
Guizhou	0.382	0.169	0.296	0.213	0.242	0.234
Yunnan	0.345	0.207	0.344	0.378	0.261	0.297
Tibet	0.100	0.165	0.100	0.900	0.118	0.144
Shaanxi	0.553	0.176	0.254	0.152	0.300	0.235
Gansu	0.167	0.196	0.202	0.139	0.162	0.247
Qinghai	0.119	0.133	0.128	0.240	0.135	0.124
Ningxia	0.131	0.196	0.129	0.103	0.151	0.193
Xinjiang	0.314	0.510	0.229	0.275	0.228	0.459

Table 4. Water use efficiency.

DMU	Score1	Score2	Score3
Beijing	1	1	1
Tianjin	1	1	1
Hebei	0.921	1	1
Shanxi	1	1	1
Inner Mongolia	1	1	1
Liaoning	0.958	1	1
Jilin	1	1	1
Heilongjiang	1	1	1
Shanghai	1	1	1
Jiangsu	1	1	1
Zhejiang	0.919	1	1
Anhui	0.718	1	1
Fujian	0.775	1	1
Jiangxi	0.709	1	1
Shandong	1	1	1
Henan	0.878	1	1
Hubei	0.739	1	1
Hunan	0.699	0.858	1
Guangdong	1	1	1
Guangxi	0.632	0.736	1
Hainan	1	0.907	1
Chongqing	0.990	1	1
Sichuan	0.768	1	1
Guizhou	0.961	1	1
Yunnan	0.898	1	1
Tibet	1	1	1
Shaanxi	0.953	1	1
Gansu	0.808	1	1
Qinghai	1	1	1
Ningxia	0.926	0.719	1
Xinjiang	0.771	1	1

Note: Score1: Evaluation results based on synthetic indexes; Score2: Evaluation results based on simplified indexes; Score3: Evaluation results based on original indexes; See Tables 1 and 5 for the definitions of synthetic, simplified, and original indexes.

As shown in the last column in Table 4, the number of original indexes is too large, relative to the number of DMUs, which yields the result that all DMUs have an efficiency value of 1. Therefore, the evaluation using original indexes is ineffective. In addition, evaluation can be done using the simplified indexes. However, there are still more than half of the provinces and municipalities with an efficiency of 1, and the scores of other provinces are very close, which indicates that the simplified indexes cannot effectively reflect the differences in water use efficiency of various provinces and municipalities. By using the multi-level entropy weight method, the evaluation results retain all the essential information of the original indicators, and avoid the problem that the number of original indexes is too large, relative to the number of DMUs. The evaluation results effectively show the difference in water use efficiency among provinces and municipalities. At the same time, the entropy method reduces the impact of industrial structure and division of labor on water use efficiency.

Table 5. Simplified indexes set.

Input	Total water consumption Water supply pipe length Water conservancy fixed asset investment Total wastewater discharge
Output	Total water resources Total GDP Total employed population Effective irrigated area Total grain output

3.3. Discussion

According to the results, the water use efficiency of Beijing, Tianjin, Shanxi, Inner Mongolia, Jilin, Heilongjiang, Shanghai, Jiangsu, Shandong, Guangdong, Hainan, Tibet and Qinghai are at optimum, which implies that the level of water management and water use technology in these regions are notably high. The water use efficiency scores of Hebei, Liaoning, Zhejiang, Chongqing, Guizhou, Shaanxi, and Ningxia are above 0.9. Therefore, the water use efficiency in these regions is relatively high but can still be further improved. However, there are many regions with an efficiency lower than 0.8, especially Hunan and Guangxi which scored below 0.7. Such regions may face serious water shortages due to water wastes, and their industrial structures are in urgent need of transformation and upgrading so that the water management efficiency can be improved.

In addition, Figure 1 shows the distribution of water use efficiency across the addressed 31 regions using synthetic indexes. On the map of water use efficiency, regions in northeast China (including the eastern part of Inner Mongolia) are more efficient in water use. Note that such regions often have sufficient water resource and modernized agriculture with higher efficiency in irrigation, which leads to their higher scores in water use efficiency [40,41]. In addition, considering China's industrial layout, agricultural products are often supplied as intermediate products to other industrial products. Some agricultural products are transferred to other provinces for further processing, which indirectly increases the total outputs in other provinces. Therefore, it is reasonable for agricultural provinces to gain higher water use efficiency since they contribute not only their own output values but also other provinces'. A similar argument can be made to reason the high scores of water use efficiency in Shandong, Shanxi, and other agricultural provinces. Moreover, the higher scores of water use efficiency in municipalities and southeastern regions in China are mainly because of industrial and population agglomeration in such regions. A higher degree of industrial and population agglomeration often leads to relatively higher social productivity and therefore, higher water use efficiency. In addition, water pollution can be treated more effectively due to sufficient investment in pollution governance in such regions. Also, the proportions of the agricultural sector in such regions are generally smaller, which somewhat contributes to their water use efficiency. Unexpectedly, the scores of water use efficiency in Tibet, Qinghai, and Guizhou are relatively high. Although the economies in these regions are considered less developed, the population densities and the scales of industry in such regions are relatively low. Therefore, water use in such regions are low as well. At the same time, the central and local governments have been emphasizing ecological governance and protection, as well as the development of environmentally friendly industries in these regions, which reduces local water use while increasing the value of output. The provinces in the middle reaches of the Yangtze River have the lowest water use efficiency. Although they have abundant water resources and an advanced water system, the over-exploitation of water resources has caused the most serious water pollution in these regions. In addition, water conservation in production is not considered as a priority in these regions, which leads to the low water use efficiency.

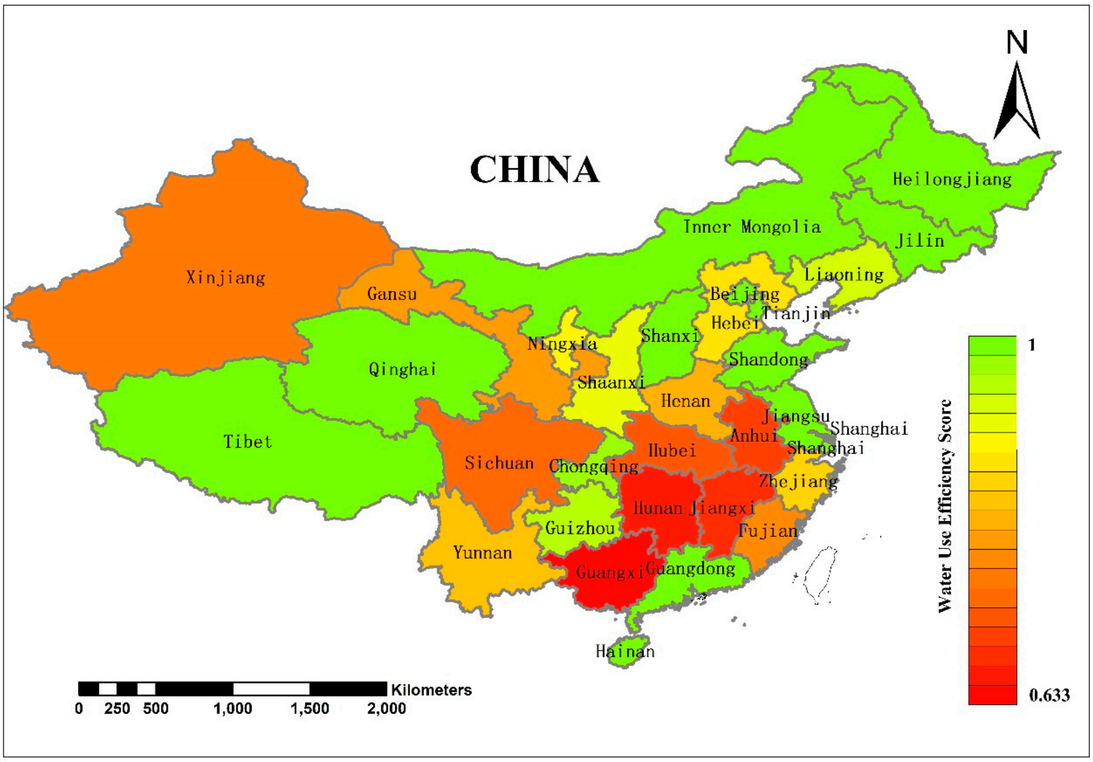

Figure 1. Water use efficiency distribution map.

4. Conclusions

Our study shows that the multi-level entropy weighted DEA model can effectively reduce the number of input and output indicators to be used in the DEA model, while retaining all the essential information from the original indicators. Moreover, the evaluation method we utilized takes account of the differences in the industrial structures and labor divisions among different provinces and municipalities, which makes our evaluation more objective and reasonable. The results of this study also suggest that there is still much room for improvement in water use efficiency, especially in terms of water conservation, across China. As the Chinese government continues to promote the supply side reform in water supply, authorities in each province and municipality should consider the distribution of population and water resource in the policy making process, instead of merely stimulating industrial development. In addition, local governments should improve the layout of industrial structure while sufficiently utilizing advanced technologies to conserve water resource and improve water use efficiency. However, our study is limited to data availability. In future studies, researchers should collect long panel data to conduct estimations in order to address the potential trend of water use efficiency. Furthermore, our study utilizes data at provincial level, which does not address the differences in water use efficiency at county level. Future research should apply the data at county level to provide a more focused analysis of the differences in water use efficiency within each province, which can help local governments to make targeted policies.

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