International Journal of Computational Intelligence Systems
Vol. 12(2), 2019, pp. 1649–1659
DOI: https://doi.org/10.2991/ijcis.d.191209.002; ISSN: 1875-6891; eISSN: 1875-6883
https://www.atlantis-press.com/journals/ijcis/

Evaluation on the Efficiency of Water-Energy-Food Nexus Based on Data Envelopment Analysis (DEA) and Malmquist in Different Regions of China

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ARTICLE INFO

Article History
Received 30 Sep 2019
Accepted 08 Dec 2019

Keywords
DEA Model
Malmquist index
W-E-F nexus
Efficiency

ABSTRACT

Water-energy-food (W-E-F) nexus is an essential element for human survival, as well as the basis for the sustainable development of regional economy and ecological environment. Water resource is an important input element of energy production and food production, which makes the W-E-F nexus become closer and more complicated. Taking water resource as the main input variable and grain as the output variable, and taking water resource and grain consumption as the main input variable and energy output as the output variable, the W-F and W/F-E coupling efficiency evaluation index system was constructed. Using data envelopment analysis (DEA) and Malmquist index model, the W-E-F coupling efficiency of 31 regions in China from 2007 to 2016 was evaluated from static and dynamic perspectives. In view of the low comprehensive efficiency in most areas, this paper gives corresponding strategies and suggestions.

1. INTRODUCTION

Water resources, energy, and food are the basic resources for human survival, and are also important research topics for sustainable development of regional economy and ecological environment [1,2]. From 1980 to 2011, there was a sense of research and project development on Water-Energy-Food (W-E-F) nexus around the world, such as Japan, India, and the USA. The nexus could be dated back to the World Economic Forum in 2008, where the global challenges related to economic development were recognized from the W-E-F nexus perspective [3,4]. At the same time, more and more international organizations and universities attempted to consider the social, political, economic, and environment for the W-E-F nexus. In 2011, the Century Economic Forum released the Global Risk Report, it is the first time to proposed the concept of water-energy-food risk group and summarize the relationship of W-E-F nexus [5–7]. In recent years, many researchers have been also conducted in-depth studies on the relationship between water, energy, and food [6,8–11]. From 2011 to 2015, more than 300 organizations and universities launched W-E-F nexus initiatives in the world and the number of W-E-F nexus publications is also increasing dramatically. Li *et al.* [12] used the system dynamics model to simulate the relationship between W-E-F, taking Beijing as an example to analyze the nexus between them. Peng [13] introduced the synergetic principle to construct a W-E-F overall analysis framework and a cross-feed correlation synergetic optimization model. Taking the Yellow River Basin as the research object, he optimized the layout of the three and predicted the demand of the three in the future.

Numerous studies on W-E-F nexus focus on interaction [4,14,15], one-way efficiency [16–18] and the nexus between the two resources [19]. For example, water, energy, and food are included in the same system study [3], sustainable development [3,4,20–22], energy utilization efficiency [20,23], and water-food coupled relationship. Liao *et al.* [24] analyzed the life-cycle water uses for energy consumption. It aims to calculate the life-cycle water usage to meet the needs from 2002 to 2015. The structural decomposition analysis is conducted to estimate the respective impacts of four driving factors, such as energy, population, water, and the economic structure. Recently, the focus of research is on the division of system boundaries and the elaboration of correlation relations [25], most of which are based on qualitative analysis methods and have local characteristics through the coordination and sustainable development of the specific case study area [10–12,14,18,19,21,26,27]. Based on input–output theory [28], Li *et al.* [29] analyzed the efficiency relationship between W-E-F in different regions of China. The total consumption of water, energy, and food expenditure and resident population were used as input indicators, and per capita GDP and environmental pollution index used as output indicators. In recent years, it has been proposed an integrated mathematical programming model for optimizing water, energy, food resources. Li *et al.* [30] developed an integrated model, called Agricultural Water-Energy-Food Sustainable Management (AWEFSM), was developed for the sustainable management of W-E-F resource in an agricultural system by non-linear programming, incorporating multi-objective programming and intuitionistic fuzzy numbers into a general framework. Xiao *et al.* [31] set the national economy of China as a whole system, and apply supply chains analysis based on the input–output

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structures, to identify the food-water linkage, food-energy linkage, and the energy-water linkage in the system. The results show that agriculture and animal husbandry contribute most use of resource in supply chains.

Data envelopment analysis (DEA) was initially developed by Charn *et al.* [32] for the purpose of evaluating the relative efficiency of similar economic production systems on the basis of multiple inputs and outputs. As an effective method, DEA is extremely useful, such as proposing a system to determine the best location for constructing agriculture-industry. Wu *et al.* [33] established the input-oriented zero-sum gains data envelopment analysis (ZSG-DEA) model, the rights of PM2.5 emission are investigated under the condition that the target total amount is fixed. It can give practical support for haze-reducing work load conducted by central and local governments of China. Chu *et al.* [34] built a slack-based measure (SBM)-DEA model, which was applied to do environmental efficiency analysis of transportation systems. The SBM-DEA model shows that the parallel computing design helps to significantly reduce calculation time when completing environmental efficiency evaluation tasks with mass data. Zhou *et al.* [35] reviewed the literature on DEA applications by mean of citation-based approaches. According to citation relationships, the network was constructed from 1996 to 2016. It found four research clusters including regional sustainability, corporate sustainability, sustainability composite indicator, and sustainability performance analysis. DEA model was widely used in many aspects of efficiency evaluation, some researchers combine the method of DEA with other quantitative analysis methods to achieve better results. DEA model is an efficient model to evaluate the efficiency, and rarely paper studies the efficiency for W-E-F system nexus by DEA. Thus, the paper adopts DEA model.

DEA model was constructed and compared from two aspects of static cross-sectional data and time series data. The DEA efficiency values in most regions of China were low, and some improvement strategies were put forward. In the literature, water resources, energy, and food resources were all used as input indicators to study the utilization efficiency of resources in various regions. But the internal coupling relationship among water resources, energy, and food is not thoroughly analyzed. Therefore, it is crucial to place W-E-F equally in one platform to get stakeholders involved, and to shift the nexus from concept to practice with decision-making. In this paper, we studies interactions in the W-E-F nexus and focuses on level partitions between factors intertwining in the nexus system to raise awareness among decision makers and to promote nexus governance. It is difficult to quantify W-E-F nexus. Based on the related two-stage DEA-Malmquist model, this paper uses water resources as the input index, food resources as the output index, water resources and food resources as the input index and energy as the output index in the second stage. We also utilizes DEA model to evaluate the cross-sectional data static benefits of W-F input–output efficiency and W/F-E input–output efficiency in various regions of China from 2007 to 2016. At the same time, the Malmquist index is used to evaluate the dynamic benefits of time series data of W-F input–output efficiency and W/F-E input–output efficiency in various regions of China from 2007 to 2016. Combining the quantitative analysis results of the two aspects, we hope to provide policies and suggestions that can effectively improve the efficiency of W-E-F in various regions of China.

The remainder of the paper is structured are follows. Section 2 presents the W-E-F nexus coupling relationship and evaluation index system. Section 3 shows the principle and application conditions of the DEA and Malmquist. Section 4 demonstrates four situations through the DEA and Malmquist model, which calculates the efficiency of W-F and W/E-F in different regions. In Section 5, by calculating efficiency value in various regions from 2007 to 2016, a comparison chart between the two is constructed and discuss the results. In the last section, we display some summaries and recommendations.

2. W-E-F NEXUS COUPLING RELATIONSHIP AND EVALUATION INDEX SYSTEM

Water, energy, and food are three kinds of natural resources that are not only the foundation of national survival, but also the foundation of regional sustainable development. With the decrease of total water resources in China, the demand for energy is increasing. At the same time, the food supply is affected by more factors and the uncertainty is greatly increased. It is necessary to study the coordination relationship among the three. Only through the coordinated development of the three can its overall efficiency be improved and more conducive to regional sustainable development. It is impossible to provide an optimal decision-making scheme only by studying the two synergy relationships of water-energy synergy, water-grain synergy, and energy-grain synergy, and it is also possible to mislead decision-making. The relationship between water, energy, and food is complex, and there are trade-offs and potential conflicts in the process of production, consumption, and management. Therefore, this paper focuses on the in-depth analysis of W-F, W-E and the synergistic relationship between W and F-E. Based on the interactive relationship among water, energy, and food, this paper constructs a core matrix diagram of W-F and W/F-E based on W-E-F nexus, as shown in Table 1.

In view of the research purpose, the practical significance, the importance and the availability of data, this paper selects agricultural water consumption, the number of employees in agricultural production and the area of irrigated farmland as input indicators for the first stage of input–output efficiency evaluation, and food as output indicators for the first stage. At the same time, the output index of the first stage is used as the input index of the second stage, forming the input index of the second stage of industrial water consumption, industrial fixed investment and food consumption of industrial production employee. And the energy output is used as the output index of the second stage. The evaluation index system of W-E-F nexus coupling efficiency is constructed, as shown in Table 2.

Table 1 Core matrix diagram of W-F, W/F-E based on W-E-F nexus.

	W	F	E
W	—	Grain growth	Hydroelectric power Exploitation
F	—	—	Bio-energy
E	—	—	—

Note: W-E-F= Water-Energy-Food.

According to the constructed evaluation index system, two stages of W-E-F nexus input–output efficiency analysis are constructed, as shown in Figure 1.

3. METHODOLOGY

3.1. DEA Model

DEA is a mathematical programming approach to evaluate the relative effectiveness of Decision-Making Unit (DMU), which is first proposed by Charn *et al.* [32]. It uses multiple inputs and outs to assess the relative efficiency of homogeneous DMUs [28]. Charnes, Cooper, and Rhodes (CCR) model and Banker, Charnes, Cooper (BCC) model are two traditional DEA models and widely used [28,36].

Assume that there are n DMUs $\left\{DMU_j : j = 1, 2, ..., n\right\}$ to be evaluated in terms of m inputs $\left(x_{ij}\,(i = 1, 2, ..., m)\right)$ and s outputs $\left(y_{rj}\,(r = 1, 2, ..., s)\right)$. x_{ij} $(i = 1, 2, ..., m)$, y_{rj} $(r = 1, 2, ..., s)$ are input and output value of DMU_j $\left(j = 1, 2, ..., n\right)$ respectively. Suppose that inputs and outputs for $DMU_j$are denoted by $x_j = \left(x_{1j}, x_{2j}, ..., x_{mj}\right)^T$ and $y_j = \left(y_{1j}, y_{2j}, ..., y_{sj}\right)^T$, $x_j > 0$, $y_j > 0$ $\left(j = 1, 2, ..., n\right)$. In the following, we introduce the CCR and BCC models.

Table 2 Evaluation index system of W-E-F nexus coupling efficiency.

Type	Name of Index	Unit
Stage 1/Input indicators	Irrigable cultivated area	Hundred million cubic meters
	Agricultural water consumption	Hundred million cubic meters
	Number of employees in agricultural	Thousands
Stage 1/Output indicators	Grain yield	Kilogram
Stage 2/Input indicators	Industrial water consumption	Hundred million cubic meters
	Number of employees in industry	Kilogram
	Fixed industrial investment	Billion
Stage 2/Output indicators	Energy output	Kilowatt

Note: W-E-F= Water-Energy-Food.

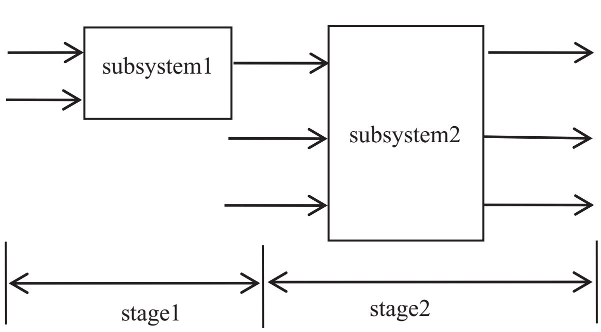

Figure 1 Two stage analysis of input–output efficiency.

3.1.1. The CCR model

CCR [32] introduced a ratio definition of efficiency, which is also called CCR ratio definition. CCR model generalizes the single-output to single-input classical engineering-science ratio definition to multiple outputs and inputs without requiring pre-assigned weights. CCR is given by the following optimization problem:

$$\max\ h_o = \frac{\sum_{r=1}^{s} u_r y_{ro}}{\sum_{i=1}^{m} v_i x_{io}} \tag{1}$$
$$\text{s.t.} \begin{cases} \dfrac{\sum_{r=1}^{s} u_r y_{rj}}{\sum_{i=1}^{m} v_i x_{ij}} \le 1, j = 1, 2, ..., n; \\ u_r \ge 0, v_i \ge 0, i = 1, 2, ..., m; r = 1, 2, ..., s \end{cases}$$

In the Model (1), the subscript o indicates the DMU under evaluation, v_i $(i = 1, 2, ..., m)$ and u_r $(r = 1, 2, ..., s)$ are the input and output weights, which is to be determined. This is well known as the CCR model, which is a fractional program, and can be converted into the following linear problem:

$$\max\ z_o = \sum_{r=1}^{s} u_r y_o \tag{2}$$
$$\text{s.t.} \begin{cases} \sum_{i=1}^{m} v_i x_{io} = 1 \\ \sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} \le 0, j = 1, 2, ..., n \\ v_i, u_r \ge 0, i = 1, 2, ..., m; r = 1, 2, ..., s \end{cases}$$

In Model (2), DMU_o is considered to be efficient if and only if $z_o^* = 1$; otherwise, it is referred to as non-efficient.

In the CCR model, constant return to scale is an implied hypothesis. That is to say, all of the DMUs have the result of optimal production scale, plus constant scaling of input and output data, and the overall efficiency. Not all of the DMUs are satisfied with the implied hypothesis in the CCR model. BCC was used to evaluate the technical effectiveness of DMUs under the assumption of variable scale compensation [37]. Water resource constraints have become a challenge to sustainable economic development. How to use water resources efficiently has become a topic discussed by both government and scholars. The paper chooses the BCC model of investment tendency to be more realistic and pursues the minimum investment under the condition of certain output.

3.1.2. The BCC model

To overcome the flaw, Banker *et al.* [38] added constraints to the CCR model, building the BCC model, which has some advantage in providing both overall technical and scale efficiencies. In the BCC model, the results of the ath input are not equal with the ath output, facilitating the application of the DEA method to the complex system, such as the W-E-F nexus coupling system.

Assuming that there are n DMUs, each DMU contains m input items and s output items, the meaning of input and output refers to

DMU's consumption of resources and resulting output. The BCC model is [38]:

$$\min \theta \tag{3}$$
$$\begin{cases} \sum_{j=1}^{n} \lambda_j x_{ij} \le \theta x_{io}, i = 1, 2, \ldots, m \\ \sum_{j=1}^{n} \lambda_j y_{rj} \ge y_{ro}, r = 1, 2, \ldots, s \\ \sum_{j=1}^{n} \lambda_j = 1 \\ \lambda_j \ge 0, j = 1, 2, \ldots, n \end{cases}$$

Model (3) can be further transformed into the following:

$$\min \theta - \varepsilon \left(\sum_{i}^{m} s_i^- + \sum_{r=1}^{s} s_r^+ \right) \tag{4}$$
$$\begin{cases} \sum_{j=1}^{m} x_{ij}\lambda_j + s_i^- = \theta x_{io}, i = 1, 2, \ldots, m \\ \sum_{j=1}^{m} y_{rj}\lambda_j - s_r^+ = y_{jo}, r = 1, 2, \ldots, s \\ \sum_{j=1}^{n} \lambda_j = 1 \\ s_i^- \ge 0; s_i^+ \ge 0; i = 1, 2, \ldots, m \\ \lambda_j \ge 0, j = 1, 2 \ldots, n \end{cases}$$

In the Model (4), $S^+ = \left(s_1^+, s_2^+, \ldots, s_s^+\right)^T, S^- = \left(s_1^-, s_2^-, \ldots, s_m^-\right)^T$ are the primal output and prime input slack vectors. Actually, Model (4) is the dual problem of Model (2) except the additional constraint $\sum_{j=1}^{n} \lambda_j = 1$. Assume that λ^0, S^{-0}, S^{+0}, θ^0 is the optimal solution of linear programming, which is the expected efficiency value. The value is in the range of 0–1. If $\theta^0 = 1$ and $S^- = S^+ = 0$, the decision unit is DEA efficient; If $\theta^0 = 1$ and $S^- \ne 0$ or $S^+ \ne 0$, the decision unit is weak DEA efficient; If the decision unit is DEA invalid, it means the input is redundancy, and the output is insufficient. When DMU is weak DEA effective and DEA ineffective, its value is not zero, indicating excessive input of resources and insufficient output. To apply the DEA method properly, all DMUs are homogeneous. The number of DMUs should not be less than twice the total number of indicators of the input and output index system.

3.2. Malmquist Index

In order to research the dynamic efficiency, the Malmquist index is mainly used. This paper also depicts the productivity with distance function. There is a production possibility set S. S represents the ability to achieve the transformation of x to y, and the point (x, y) in the S at which it can achieve the largest output y in every given input x is in the production frontier. With production possibility set S, the distance function in time t (1, 2, ..., T) is shown in Eq. (6).

$$S = \{(x, y) : x \to y\} \tag{5}$$

$$D(x, y) = \inf\{\theta : (x, y|\theta) \in S\} = (\theta : (x, \theta y) \in S)^{-1} \tag{6}$$

where $D(x, y) \le 1$, if and only if point $(x, y) \in S$; and $D(x, y) = 1$, if and only if point (x, y) is in the production frontiers. The Malmquist index is defined as:

$$M\left(x^{t+1}, y^{t+1}, x^t, y^t\right) = \left[\left(\frac{D^t\left(x^{t+1}, y^{t+1}\right)}{D^t\left(x^t, y^t\right)}\right) \times \left(\frac{D^{t+1}\left(x^{t+1}, y^{t+1}\right)}{D^{t+1}\left(x^t, y^t\right)}\right)\right]^{\frac{1}{2}} \tag{7}$$

We have divided it into two functions, D^t and D^{t+1}, in time t and $t+1$. Eq. (7) has two parts. The first one is the percentage in the distance function D^t, between the possible output in time $t+1$ and its real time t. The second part is the distance function D^{t+1}, between the real output in $t+1$ and the possible in time t.

Fare and Grosskopf [39] constructs the technical Malmquist index from t to $t+1$ and decomposes it into two parts: comprehensive technical efficiency (EC) and technical progress change (TE). The technical efficiency change can be further decomposed into pure technical efficiency change (PTE) and scale efficiency change (SE).

$$EC = \frac{D^{t+1}\left(x^{t+1}, y^{t+1}\right)}{D^t\left(x^t, y^t\right)} \tag{8}$$

$$TE = \left(\frac{D^t\left(x^{t+1}, y^{t+1}\right)}{D^{t+1}\left(x^{t+1}, y^{t+1}\right)} \times \frac{D^t\left(x^t, y^t\right)}{D^{t+1}\left(x^t, y^t\right)}\right)^{\frac{1}{2}} \tag{9}$$

The Malmquist index is expressed as Eq. (10):

$$M\left(x^{t+1}, y^{t+1}, x^t, y^t\right) = EC \times TE = (PTE \times SE) \times TE \tag{10}$$

The meaning of the expression in the formula is:

1. Malmquist index indicates productivity changes, $M > 1$ indicates productivity level increases, $M < 1$ indicates productivity level decreases, and $M = 1$ indicates productivity level remains unchanged.
2. EC indicates the comprehensive technical efficiency, indicating the advantages and disadvantages of industrial and enterprise management decisions and resource allocation, $EC > 1$ indicates the improvement of EC, management methods, and resource allocation, $EC < 1$ indicates the decline of technical efficiency, inappropriate management decisions, and insufficient utilization of resources, and $EC = 1$ indicates that the EC remains unchanged.
3. TE indicates changes in technological progress, that is, changes in technological innovation and industrial production technology. $TE > 1$ indicates progress in production technology, $TE < 1$ indicates decline in production technology, and $TE = 1$ indicates that technological progress remains unchanged.

When the value of the Malmquist index is greater than one, the W-E-F coupling efficiency increases. If the value of the Malmquist index is less than one, then the W-E-F coupling efficiency decreases.

4. CASE STUDY

In this paper the data are from China Statistical Yearbook and China Energy Statistics Yearbook from 2007 to 2016. Water, energy, and food from 31 provinces are selected as the feasible sets of input and output data in China.

4.1. Static Evaluation of W-F Coupling Efficiency in Different Regions Based on DEA

Input indicators. The direct input index is the consumption of water resources in the agricultural production activities of each region in that year, that is, the agricultural water consumption of each region. The indirect input index is the number of employees in agricultural production, mainly because population variables are the core elements of regional sustainable development, and effective labor force is one of the core input variables of food and energy output. Irritable cultivated land area refers to the cultivated land area that has a certain amount of water source, is leveled with irrigation projects or equipment, and can be irrigated normally in the general year. Agricultural water includes farmland irrigation water, forest and fruit land irrigation water, grassland irrigation water, fish pond water supplement, and livestock and poultry water.

Output indicators. Food output refers to the total amount of gain produced by agricultural producers and operators in the year. According to the harvest season, it includes summer harvest grain, early season rice, and autumn harvest grain, and according to the variety of crops, it includes grains, potatoes, and beans. In this paper, the food output data mainly collected grain.

In this paper, the DEA method and DEAP 2.1 software are used to calculate the selected W-F data from 2007 to 2016, and the coupling efficiency table shown in Table 3 is obtained.

It can be seen from the Table 3 that the W-F efficiency values in Liaoning, Jilin, Heilongjiang, Henan, and Chongqing are all between 0.8 and 1, and the comprehensive efficiency values are relatively high. The main reason is that these areas are relatively abundant in water resources. With the continuous improvement of technology, the efficiency of production was improved. At the same time, the scale and efficiency of food production in these areas are relatively large. In Hebei, Shanxi, Jiangxi, Shandong, Sichuan, and other regions, the comprehensive efficiency value is between 0.55 and 0.75. These regions are mainly affected by the endowment of water resources and other industry demand for water resources, making their overall efficiency low. Although Sichuan, Jiangsu, Zhejiang, Anhui, and other places are relatively rich in water resources, the scale benefit of grain production is not high due to topographical factors, resulting in low relative benefit value. Beijing, Tianjin, Shanghai, and other places have efficiency values ranging from 0.2 to 0.55. The main reason for the relatively comprehensive efficiency values is that these areas are economically developed, the economic benefits from gain growth are low, and water resources were dominated by other industry.

According to DEA model, $EC = PTE \times SE$, and the level of comprehensive efficiency value is affected by both pure technical efficiency value and scale efficiency value. By the software calculation results, this paper constructs a two-dimensional scatter diagram from PTE, and SE perspectives, as shown in Figure 2.

As can be seen from Figure 2, PTE, and SE values are higher in Jilin, Shandong, Chongqing, Sichuan, and Hunan, and their comprehensive efficiency values are also higher. Tianjin, Shanghai, Tibet, Beijing, and Qinghai have higher PTE values but lower SE values. Qinghai can improve its scale benefit and thus its comprehensive

Table 3 2007–2016 W-F coupling efficiency value of each region.

Province	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
Beijing	0.395	0.307	0.399	0.348	0.342	0.315	0.083	0.208	0.24	0.218
Tianjin	0.382	0.378	0.388	0.413	0.436	0.427	0.076	0.476	0.452	0.446
Hebei	0.582	0.583	0.585	0.606	0.687	0.638	1	0.663	0.61	0.639
Shanxi	0.632	0.649	0.64	0.697	0.741	0.8	0.122	0.772	0.664	0.687
Inner Mongolia	0.376	0.383	0.412	0.402	0.401	0.422	0.111	0.459	0.46	0.445
Liaoning	0.823	0.721	0.721	0.71	0.73	0.672	0.204	0.541	0.642	0.652
Jilin	1	1	1	1	1	1	0.308	1	1	1
Heilongjiang	0.707	0.686	0.767	0.719	0.672	0.62	0.139	0.508	0.529	0.466
Shanghai	0.392	0.349	0.449	0.405	0.393	0.394	0.082	0.286	0.297	0.264
Jiangsu	0.625	0.617	0.669	0.692	0.713	0.708	0.118	0.734	0.695	0.671
Zhejiang	0.584	0.581	0.608	0.62	0.557	0.539	0.14	0.513	0.521	0.528
Anhui	0.716	0.72	0.762	0.775	0.784	0.79	0.104	0.681	0.64	0.623
Fujian	0.401	0.371	0.418	0.387	0.373	0.381	0.063	0.305	0.299	0.293
Jiangxi	0.726	0.675	0.787	0.73	0.73	0.686	0.137	0.773	0.732	0.742
Shandong	1	1	1	1	1	1	0.388	1	1	1
Henan	1	1	1	1	1	1	0.184	1	1	1
Hebei	0.71	0.596	0.704	0.678	0.705	0.69	0.115	0.609	0.603	0.548
Hunan	0.751	0.755	0.914	0.898	0.91	1	0.197	0.905	0.784	0.786
Guangdong	0.621	0.411	0.478	0.469	0.47	0.489	0.086	0.47	0.456	0.468
Guangxi	0.632	0.565	0.678	0.62	0.569	0.583	0.121	0.534	0.514	0.512
Hainan	0.597	0.375	0.454	0.394	0.376	0.374	0.084	0.285	0.294	0.262
Chongqing	1	1	1	1	1	1	0.161	0.978	0.905	0.924
Sichuan	0.814	0.817	0.924	0.949	0.982	0.931	0.145	0.925	0.857	0.855
Guizhou	0.879	0.77	0.814	0.744	0.487	0.626	0.108	0.706	0.654	0.664
Yunnan	0.571	0.503	0.635	0.533	0.556	0.583	0.121	0.597	0.571	0.789
Tibet	0.458	0.351	0.328	0.299	0.289	0.312	0.053	0.25	0.243	0.327
Shaanxi	0.567	0.546	0.638	0.659	1	0.713	0.122	0.717	0.697	0.682
Gansu	0.417	0.371	0.43	0.456	0.442	0.475	0.09	0.456	0.449	0.431
Qinghai	0.317	0.136	0.158	0.162	0.154	0.16	0.044	0.173	0.164	0.154
Ningxia	0.485	0.424	0.512	0.499	0.451	0.474	0.089	0.478	0.46	0.461
Xinjiang	0.167	0.154	0.215	0.196	0.181	0.176	0.038	0.135	0.152	0.151

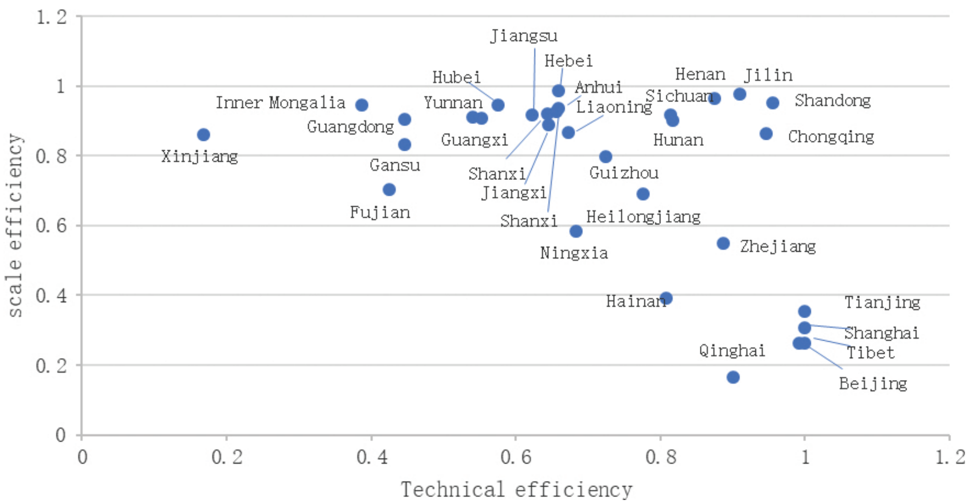

Figure 2 2007–2016 scatter diagram of pure technical efficiency change-scale efficiency change (PTE-SE) two-dimensional structure under W-F coupling efficiency.

efficiency value, but the other four regions only need to complete grain production due to their relatively developed economy and the small proportion of agriculture in the total economy. All other regions should increase the pure technical efficiency value to improve the comprehensive efficiency value.

4.2. Dynamic Evaluation of W-F Coupling Efficiency in Different Regions Based on Malmquist Index

To research the W-F coupling efficiency more comprehensively and deeply, this paper uses Malmquist index and DEAP2.1 software to make a dynamic evaluation of the W-F coupling efficiency in various regions of China from 2007 to 2016, as shown in Table 4.

Malmquist index value = EC * TE, judging from the above table, the TE values of different regions are not much different, which indicates that the technology in the grain production process in different regions of China is relatively balanced, and the technology has gradually improved in the past decade. The influence of Malmquist index value is mainly caused by the change of EC. However, the comprehensive technical value = PTE * SE, which is caused by the differences in the endowment of water resources and topography of each region. It influences the scale efficiency value and affects the comprehensive technical value.

The Malmquist index values in Beijing, Heilongjiang, Shanghai, Fujian, Hubei, Guangdong, Hainan, Guizhou, Tibet, and Qinghai regions are less than 1, indicating that the grain productivity level in these regions has declined. So, the other regions need to continue to increase their productivity if they want to play the role of the grain production base, such as Heilongjiang and Guizhou.

Table 4 2007–2016 W-F coupling efficiency Malmquist index of each region.

Province	EC	TE	PTE	SE	Mal
Beijing	0.936	1.034	1	0.936	0.968
Tianjin	1.017	1.022	1	1.017	1.039
Hebei	1.011	1.041	1.01	1.001	1.053
Shanxi	1.009	1.016	1.016	0.994	1.026
Inner Mongolia	1.019	1.035	1.019	1	1.054
Liaoning	0.974	1.036	0.978	0.997	1.01
Jilin	1	1.038	1	1	1.038
Heilongjiang	0.955	1.036	0.996	0.958	0.99
Shanghai	0.957	1.04	1	0.957	0.995
Jiangsu	1.008	1.011	0.994	1.014	1.019
Zhejiang	0.99	1.105	1.03	0.961	1.094
Anhui	0.985	1.029	0.98	1.005	1.014
Fujian	0.966	1.034	0.986	0.98	0.998
Jiangxi	1.002	1.021	1.002	1	1.023
Shandong	1	1.126	1	1	1.126
Henan	1	1.053	1	1	1.053
Hebei	0.972	1.028	0.971	1	0.999
Hunan	1.005	1.046	0.994	1.012	1.051
Guangdong	0.969	1.026	0.972	0.997	0.994
Guangxi	0.977	1.039	0.982	0.995	1.014
Hainan	0.912	1.036	0.945	0.965	0.946
Chongqing	0.991	1.013	1	0.991	1.004
Sichuan	1.006	1.017	0.993	1.013	1.023
Guizhou	0.969	1.023	0.983	0.986	0.992
Yunnan	1.037	1.038	1.04	0.997	1.076
Tibet	0.963	1.034	1	0.963	0.996
Shaanxi	1.021	1.015	1.026	0.995	1.036
Gansu	1.004	1.025	1.008	0.996	1.029
Qinghai	0.923	1.05	1.006	0.917	0.969
Ningxia	0.994	1.027	1.009	0.986	1.021
Xinjiang	0.988	1.036	0.987	1.001	1.024

Notes: EC = comprehensive technical efficiency; PTE = pure technical efficiency change; SE = scale efficiency change; TE = technical progress change.

4.3. Static Evaluation of W/F-E Coupling Efficiency in Different Regions Based on DEA

Input indicators. It includes industrial water consumption, industrial employee's food consumption, and industrial fixed investment. Industrial water refers to the water used by industrial and mining enterprises in manufacturing, processing, cooling, air conditioning, purification, washing, and other aspects in the production process, excluding the amount of reused water within the enterprise according to the amount of new water taken. The food consumption of industrial workers was obtained by multiplying the annual food consumption per capita in the statistical yearbook by the population. Investment in energy fixed assets (excluding farmers) includes coal mining and washing industry, oil and gas mining industry, oil and coking processing industry and electricity, heat and gas production, and supply industry.

Output indicators. The total of energy production refers to the total of primary energy production in a certain period. This indicator is the comprehensive index that measures a country's energy production level, scale, and development speed. Primary energy includes raw coal, crude oil, natural gas, hydropower, nuclear energy, and other power energy. But it excluding the utilization of low calorific value fuel production, solar thermal energy, and secondary energy production converted from primary energy processing.

The data of W/F-E from 2007 to 2016 were selected for calculation, and the coupling efficiency table shown in Table 5 was obtained.

As can be seen from Table 5, Shanxi, Xinjiang, and Inner Mongolia have higher comprehensive efficiency values, and the comprehensive efficiency values of Inner Mongolia show a linear growth trend. The comprehensive efficiency values of Ningxia and Yunnan are the same, while those of other regions are showing a downward trend.

As can be seen from Figure 3, PTE, and SE values in Xinjiang, Shanxi, Shaanxi, and other places are very high. The SE values in Tibet, Hainan, Shanghai, and Beijing are relatively low, and the scale effect of energy production is relatively poor. The PTE value and SE value in Jiangsu, Inner Mongolia, Shandong, and Ningxia Regions are in the middle and deserve the further promotion. While the rest of the regions need to further improve its pure technical efficiency to make the overall technical efficiency value.

4.4. Dynamic Evaluation of W/F-E Coupling Efficiency in Different Regions Based on the Malmquist Index

To study the W/F-E coupling efficiency more comprehensively and deeply, this paper uses Malmquist index and DEAP 2.1 software to dynamically evaluate the W/F-E coupling efficiency in various regions of China from 2007 to 2016, as shown in Table 6.

Table 6 shows that the Malmquist index of Hebei, Jilin, Heilongjiang, Jiangsu, Jiangxi, Shandong, Guangdong, Guangxi, Hainan, and Sichuan regions is less than 1. It indicates the energy productivity of these regions has declined in the past decade, mainly due to the influence of the comprehensive efficiency value, which is affected by the scale efficiency.

5. DISCUSSION

This paper evaluates the input–output efficiencies of W-F and W/F-E from 2007 to 2016 by using DEA-Malmquist index model. By calculating the geometric mean value of W-F comprehensive efficiency value and the geometric mean value of W/F-E comprehensive efficiency value in various regions from 2007 to 2016, a comparison chart between the two is constructed, as shown in Figure 4.

Table 5 | 2007–2016 W/E-F coupling efficiency value of each region.

Province	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
Beijing	0.239	0.336	0.335	0.412	0.36	0.16	0.184	0.087	0.132	0.122
Tianjin	1	1	1	1	1	1	1	0.277	0.308	0.348
Hebei	0.726	0.672	0.987	0.761	0.917	0.501	0.517	0.174	0.17	0.159
Shanxi	1	1	1	0.817	0.941	0.896	0.942	1	1	1
Inner Mongolia	0.546	0.584	0.554	0.462	0.593	0.642	0.604	0.946	0.991	0.961
Liaoning	0.517	0.527	0.48	0.359	0.497	0.298	0.32	0.155	0.182	0.194
Jilin	0.39	0.358	0.36	0.245	0.383	0.282	0.18	0.105	0.102	0.094
Heilongjiang	0.728	0.663	0.655	0.493	0.571	0.373	0.31	0.206	0.206	0.189
Shanghai	0.607	0.693	0.551	0.674	1	0.371	0.42	0.176	0.175	0.157
Jiangsu	1	1	1	1	1	0.713	0.524	0.209	0.204	0.242
Zhejiang	0.597	0.79	0.907	0.966	0.939	0.427	0.423	0.162	0.2	0.197
Anhui	0.324	0.438	0.582	0.487	0.615	0.403	0.353	0.348	0.365	0.346
Fujian	0.399	0.379	0.399	0.348	0.438	0.346	0.387	0.164	0.174	0.175
Jiangxi	0.511	0.558	0.395	0.472	0.48	0.183	0.161	0.126	0.099	0.115
Shandong	1	1	1	0.961	0.963	0.541	0.549	0.267	0.264	0.262
Henan	0.583	0.544	0.577	0.695	0.788	0.314	0.293	0.267	0.193	0.161
Hebei	0.633	0.758	0.69	0.665	0.706	0.279	0.268	0.174	0.14	0.132
Hunan	0.39	0.374	0.476	0.424	0.426	0.2	0.176	0.132	0.105	0.099
Guangdong	0.763	0.757	0.697	0.669	0.86	0.453	0.281	0.144	0.144	0.138
Guangxi	0.345	0.505	0.501	0.484	0.467	0.261	0.181	0.101	0.085	0.084
Hainan	0.618	0.561	0.449	0.467	0.36	0.197	0.215	0.084	0.096	0.106
Chongqing	0.289	0.372	0.341	0.302	0.343	0.182	0.198	0.15	0.166	0.169
Sichuan	0.523	0.592	0.606	0.49	0.484	0.382	0.274	0.164	0.167	0.188
Guizhou	0.677	0.668	0.788	0.573	0.426	0.433	0.271	0.392	0.362	0.368
Yunnan	0.388	0.481	0.46	0.389	0.445	0.448	0.48	0.228	0.219	0.248
Tibet	0.118	0.097	0.088	0.07	0.083	0.067	0.052	0.019	0.025	0.044
Shaanxi	0.77	0.781	0.897	0.829	0.857	1	1	1	1	1
Gansu	0.438	0.436	0.323	0.251	0.351	0.334	0.273	0.124	0.126	0.124
Qinghai	0.897	1	1	1	1	1	1	0.363	0.269	0.292
Ningxia	0.524	0.566	0.492	0.471	0.595	0.603	0.704	0.426	0.407	0.468
Xinjiang	0.929	1	1	0.763	0.819	1	1	1	1	1

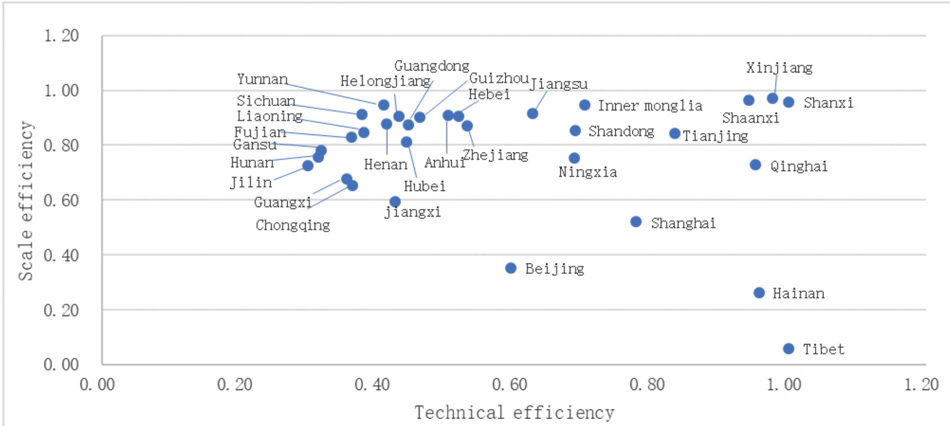

Figure 3 2007–2016 scatter diagram of pure technical efficiency change-scale efficiency change (PTE-SE) two-dimensional structure under W/F-E coupling efficiency.

Table 6 2007–2016 W/F-E coupling efficiency Malmquist index of each region.

Province	EC	TE	PTE	SE	Mal
Beijing	0.928	1.197	1.077	0.862	1.111
Tianjin	0.889	1.178	0.936	0.95	1.048
Hebei	0.845	1.147	0.865	0.977	0.969
Shanxi	1	1.153	1	1	1.153
Inner Mongolia	1.065	1.17	1.066	0.998	1.246
Liaoning	0.897	1.165	0.947	0.947	1.044
Jilin	0.853	1.129	0.929	0.918	0.963
Heilongjiang	0.861	1.152	0.902	0.954	0.991
Shanghai	0.861	1.212	1.014	0.849	1.044
Jiangsu	0.854	1.126	0.872	0.98	0.962
Zhejiang	0.884	1.172	0.912	0.969	1.037
Anhui	1.007	1.143	1.022	0.986	1.151
Fujian	0.913	1.146	0.95	0.961	1.046
Jiangxi	0.847	1.179	0.915	0.926	0.999
Shandong	0.862	1.155	0.869	0.991	0.995
Henan	0.867	1.173	0.881	0.984	1.017
Hebei	0.84	1.192	0.89	0.944	1.001
Hunan	0.858	1.171	0.924	0.929	1.006
Guangdong	0.827	1.159	0.85	0.974	0.959
Guangxi	0.855	1.147	0.928	0.921	0.981
Hainan	0.822	1.149	1	0.822	0.945
Chongqing	0.942	1.159	1.007	0.936	1.092
Sichuan	0.893	1.116	0.906	0.985	0.997
Guizhou	0.935	1.123	0.947	0.987	1.05
Yunnan	0.952	1.127	0.975	0.976	1.073
Tibet	0.897	1.125	1	0.897	1.009
Shaanxi	1.029	1.176	1.026	1.003	1.211
Gansu	0.87	1.159	0.921	0.944	1.008
Qinghai	0.883	1.133	0.974	0.907	1.001
Ningxia	0.988	1.135	0.997	0.991	1.121
Xinjiang	1.008	1.174	1.004	1.004	1.184

Notes: EC = comprehensive technical efficiency; PTE = pure technical efficiency change; SE = scale efficiency change; TE = technical progress change.

As can be seen from Figure 4, there are still many problems in W-F and W/F-E in the demand and utilization efficiency of water resources in various regions of China.

1. There is no region in the range of 0.8 ≤ W-F efficiency ≤ 1 and 0.8 ≤ W/F-E efficiency ≤ 1, indicating that there is still much room for improvement in the utilization efficiency of water resources in both agricultural production and energy production in China. Jiangsu, Shaanxi, Shanxi, and other regions can improve the technical efficiency and scale efficiency, and then improve the overall efficiency value.
2. In the range of 0.5 ≤ W-F efficiency ≤ 1 and 0 ≤ W/F-E efficiency ≤ 0.5, there are 15 regions like Guangxi, Yunnan, Heilongjiang, Zhejiang, Hubei, Anhui, Guizhou, Liaoning, Hebei, Jiangxi, Sichuan, Henan, Hunan, Chongqing, and Jilin. Jilin, Chongqing, and Hunan have relatively high W-F efficiency values, while the relatively low W/F-E efficiency values can give full play to their advantages and continue to maintain the high efficiency of grain production. In Henan, Shandong, and Sichuan, the W-F efficiency is relatively high, while the W/F-E efficiency is relatively common. Under the premise of keeping its grain production efficient, water resources should be rationally distributed through technical means to continuously improve its energy production efficiency. The W-F and W/F-E efficiency values in Jiangxi, Liaoning, Heilongjiang, Anhui, Hubei, Yunnan, Zhejiang, Guizhou, and other regions are all around 0.5. These regions can first choose one direction to make breakthroughs and improve their efficiency values. *In section* 5, Heilongjiang and Liaoning are relatively rich in water resources and can be positioned as grain production bases to strive to improve the efficiency of grain production scale in the region. Zhejiang Province is located in the coastal area and can vigorously develop energy production efficiency, actively develop the development of wind power, water power and nuclear power, and further improve its energy production efficiency.
3. In the range of 0 ≤ W-F efficiency ≤ 0.5 and 0 ≤ W/F-E efficiency ≤ 0.5, there are 7 regions like Guangdong, Gansu, Hainan, Shanghai, Fujian, Beijing, and Tibet, all of which are relatively low. Guangdong, Shanghai, Beijing, and Fujian are well-developed region, while grain production and energy production account for less of the total economy and contribute less to economic development. The main development path is to fulfill local basic food and energy needs. Because of their geographical factors, Tibet and Gansu are relatively poor in water resources and natural resources, and their efficiency values are relatively low, so they can be improved through technical means.

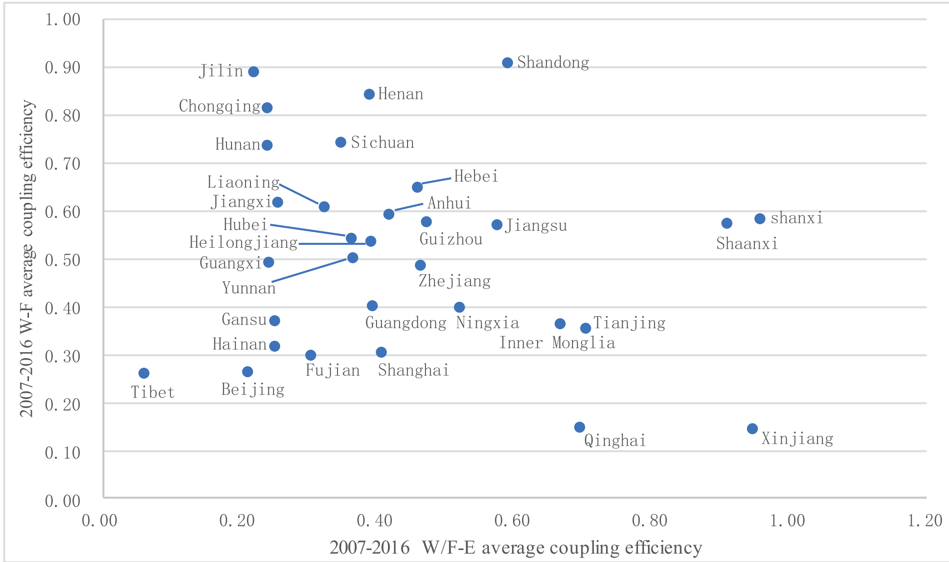

Figure 4 2007–2016 scatter diagram of pure technical efficiency change-scale efficiency change (PTE-SE) two-dimensional structure under W-F and W/F-E coupling efficiency.

4. Within the range of 0 ≤ W-F efficiency ≤ 0.5 and 0.5 ≤ W/F-E efficiency ≤ 1, there are 4 regions like Inner Mongolia, Tianjin, Qinghai, and Xinjiang. Inner Mongolia, Xinjiang, and Qinghai are relatively rich in natural resources, we can actively improve their technical efficiency, further improve the energy production efficiency and form the main energy export places in our country. Tianjin is mainly due to its high technical efficiency and high energy production efficiency. It should actively explore the development and production of new energy and make contributions to the regeneration of water resources.

According to the Malmquist index of W-F and W/F-E, Heilongjiang, Guangdong, and Hainan need to invest in pure technology in both food production and energy production to improve their overall efficiency.

6. CONCLUSIONS AND FUTURE DIRECTIONS

6.1. Conclusions

In this paper, DEA and Malmquist method were used to evaluate the coupling efficiency of W-E-F in various regions of China from 2007 to 2016, and the discussions were conducted from three perspectives, including sectional data, time series data, and the comparison between the two. Based on the results of the above empirical analysis, we can draw the following conclusions:

The analysis results of the cross-section data show that, except for Beijing, Tianjin, Hainan, Qinghai, and Ningxia, the DEA efficiency is still low in most areas of China, and shows the characteristics of polarization. From the perspective of the changes of ranking every year, most of the region's rankings are unchanged or rise, only four areas in the drop, shows that the policy of W-E-F is failed to promote regional W-E-F coupling efficiency improved, but it will help to maintain the status.

The results of time series data show that, except Qinghai, Hainan, and Xinjiang, the coupling efficiency of W-E-F in most regions in China is rising continuously. Based on the elevation in efficiency between 2007 and 2016, the regions were divided into four categories. By decomposing DEA efficiency value into PTE and SE, it can be seen that the scale efficiency value is rising in most regions of China, while the PTE is at a low level, indicating that the region is a slow variable restricting the realization of DEA efficiency in this region.

Finally, the main factors affecting the fluctuation region difference of coupling efficiency are discussed by the Malmquist index. On the one hand, the industrial structure has always been a factor affecting regional efficiency, and optimizing industrial structure becomes the important way to enhance the coupling efficiency. On the other hand, the innovation of operation and the technical promotion are other factors that have a great effect on coupling efficiency. To improve average regional technical levels, it is necessary to improve the quality of the whole people using training course. Because of the precise and comprehensive data, the coupling system is particularly suitable at the provincial levels. In this paper, the utilization efficiency of resources in different areas was compared. It is able to learn about their trends during constant periods with DEA model. By using the Malmquist index, the dynamic change of resource utilization is studied and compared. Some suggestions for improving W-E-F coupling efficiency are put forward.

6.2. Future Directions

Water, energy, and food resources are inextricably linked. The existing literature shows that the researches have been toward understanding, identifying and quantifying the interrelationships on the W-E-F nexus to identify consistent and well-rounded governance solutions. The approach proposed in this study provides a common framework for future research. There are some limitations to this paper. On the one hand, it uses a feasible method to calculate the coupling efficiency value depending on considering the region as a "black-box," but we cannot completely avoid the issue that each DMU is valid. On the other hand, the output index of the model was mainly expected output, but there are still many undesirable outputs in the W-E-F nexus, such as waste gas, waste water, and waste solid material.

Based on the results of this paper, future research should focus on three aspects. First, the current regional research does not consider difference industrial structures among different regions. It may not be accurate to treat all regions as homogeneous DMUs. In future research, we can try to use non-homogeneous DEA models to evaluate the coupling efficiency. Second, the existing literature mostly considers the region as a "black-box" and future research could use network DEA models to break the box for further study. Third, until now the sustainability of social development has been under studied, so the future researches should consider using indicators of social welfare.

CONFLICT OF INTEREST

The authors declare that they have no conflict of interest.

AUTHORS' CONTRIBUTIONS

Tianming Zhang wrote the paper. Yejun Xu designed the topic and made the revision of the paper.

ACKNOWLEDGMENTS

This study has been funded by National Key R&D Program of China (Grant No. 2017YFC0404600/2017YFC0404601). The Fundamental Research Funds for the Central Universities under Grant Numbers 2019B69314. Postgraduate Research & Practice Innovation Program of Jiangsu Province under Grant Numbers SJKY19_0402. Soft science research project of Wuxi association for science and technology under Grant Numbers KX-18-B14.

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