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Research Article

Research on World Food Production Efficiency and Environmental Sustainability Based on Entropy-DEA Model

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At present, the contradiction between the high efficiency of the world's food production and environmental pollution is becoming increasingly prominent. In order to study the related issues of the world's food production efficiency and sustainability, this paper uses the method of entropy weight to extract 5 indicators as the environmental pollution assessment model from the environmental pollution of agricultural production, scores 10 major agricultural production countries in the world, and obtains the environmental pollution index. Subsequently, the DEA model was established for these countries, the environmental pollution index was included into the production efficiency system as an unexpected output, the Malmquist index was established to describe the changes in agricultural production efficiency from 2010 to 2018, and the cluster analysis was carried out for it. Subsequently, the OSL and Tobit models were used for regression of the influencing factors. In addition, the comprehensive evaluation model of efficiency and sustainability was established by controlling the amount of fertilizer used, which was applied in different countries.

1. Introduction

With the continuous development of the current world economy, food production is becoming more and more efficient, and the food produced is enough to feed every individual in the world. However, 821 million people still suffer from the food hunger crisis worldwide [1, 2]. The current food system is well illustrated by the increasing global environmental disruption to produce adequate food, which includes a series of consumption such as greenhouse gas emissions, deforestation, and agricultural irrigation [3–7]. In studying food production systems, it is of great importance to rationally evaluate and improve the current global food system, on the one hand, considering the advantages of high efficiency for food production under the current model and, on the other hand, focusing on the environmental sustainability issues due to high efficiency [8, 9].

Due to the differences of geographical and climatic factors and customs preferences, different countries have different focus of agricultural production, and there are obvious differences in environmental factors such as planting, animal husbandry, and fishery [10, 11]. The LCA method is often used to evaluate the environmental pollution of crops in the whole life cycle [12, 13]. However, agricultural production and consumption are characterized by a large time span, and this activity is constantly changing, so it is difficult to measure. In the aspect of objective comprehensive evaluation, the entropy weight method can better measure the existing statistical data and get better results [14–16]. In the aspect of agricultural production efficiency, the DEA method is often used to measure the efficiency and productivity between similar decision-making units. By adding various constraints on the basis of the DEA method, more production efficiency models can be obtained to solve efficiency problems in various situations [17–19].

In this review, we first provide an explanation for the production efficiency and sustainability of the current global food system based on the use of the entropy weight method to establish an evaluation system for environmental pollution and the introduction of the EPI as a measure, followed by the use of the DEA model to establish a model for the evaluation of the efficiency of global food production and the inclusion of the EPI as an undesired output into production system when the model of SBM hyper efficiency is established. After that, two methods, OLS and Tobit, were used to analyze the factors affecting the efficiency of global food production by using fertilizers as hubs to connect the environmental pollution assessment model with the food production efficiency model, respectively, and then, agricultural efficiency and sustainability in representative regions were summarized, and the model was applied to different developing and developed countries, thus fully illustrating model stability and fitness. Finally, corresponding improvement measures and policy recommendations are proposed, which will be highly instructive for agricultural sustainable development.

2. Data Sources and Basic Assumptions

The data in this paper come from Question E of the 2021 American College Students Mathematical Modeling Competition and the statistics of the World Bank. In order to solve the problem, we make assumptions as follows: (i) assume that the data consulted are true and reliable; (ii) assume there is no emergency that affects the agricultural system; (iii) assume there is no geographic influence in agricultural production; and (iv) we only consider the world's major food producing countries as the evaluation object and ignore the small food producing countries.

3. Environmental Pollution Assessment Model

The current world agricultural system has successfully fed more than 70 billion people, but it has paid a huge price for the deterioration of the world's environment. It is pointed out that 25%–33% of greenhouse gases come from agricultural activities such as fertilization, cultivation, production, and incineration in Figure 1 which reflects the global trend of changes in agricultural CO_2 emissions and grain production in recent years [20]. Although the growth rate of agricultural CO_2 emissions in recent years has decreased, the total amount is still at a high level. According to relevant research, the atmospheric CO_2 concentration will reach more than 450 ppm in 2050. The rise of sea level and abnormal temperature caused by greenhouse gases has further caused serious damage to human agricultural production [21].

With the increasingly modern cities and the growth of population, the world's fresh water demand is also rising gradually. At the same time, the consumption of fresh water resources by agricultural activities cannot be ignored. Irrigation water is more than any other human activities. The regeneration ability of water resources is closely related to the stability of the food system. The current global regional food production system is in an unbalanced state. In addition to the production of necessary crops (such as rice, wheat, and cotton), it also invests a large amount of water resources into the production of inefficient food (such as avocado in Mexico). Even with the same kind of crops, the water productivity in developed countries will be much higher than that in developing countries. Therefore, choosing crops with high water productivity can not only relieve the pressure of water resources but also produce more food for food shortage areas [22, 23].

In order to meet the growing demand for planting, private growers and small-scale growers, in order to seize the agricultural market, burned forests on a large scale to quickly obtain arable land. In Indonesia, for example, before burning, people drain the swamp through canals and then cut down the trees to facilitate subsequent burning. When the forest is burned, the burning vegetation and roots ignite the coal buried underground, which releases a large amount of carbon dioxide [24]. This behavior has led to a significant decline in biodiversity and increased the risk of alien species invasion. And the reduction of the original forest also makes the adverse environmental phenomenon occur frequently.

Fertilizer is the most important part of agricultural production. For a long time, it has become a common phenomenon that the amount of fertilizer is large and the utilization rate is low. This low efficiency and high consumption mode of fertilizer application not only increases the cost of agricultural production but also causes extremely bad environmental pollution. It also increases the content of nitrogen in the soil. With the surface runoff polluting the surface water and underground water, the pollution of nitrates will be expanded, and the human cells may become cancer.

In summary, the current agricultural production pays attention to high efficiency while ignoring the low sustainability risk brought by it. This production mode is based on the future of the global environment as the overdraft cost, so it is particularly important to make an objective assessment of global environmental pollution.

3.1. Environmental Pollution Index.

3.1. Environmental Pollution Index. In this paper, an objective weighting method, i.e., the entropy weight method, is adopted to give weight to each index, respectively, according to the degree of variation of each index, so as to obtain a comprehensive index of agricultural environmental pollution.

First of all, the agricultural irrigation area, CO_2 emission, deforestation area, and fertilizer use amount of each country are standardized in four indicators:

$$
\begin{aligned}
X_{ij} &= \frac{\alpha_{ij} - \min\left(\alpha_{ij}\right)}{\max\left(\alpha_{ij}\right) - \min\left(\alpha_{ij}\right)} + 1, \\
p_{ij} &= \frac{x_{ij}}{\sum_{i=1}^{n} x_{ij}}.
\end{aligned} \tag{1}
$$

The normalized matrix P of the original matrix is as follows:

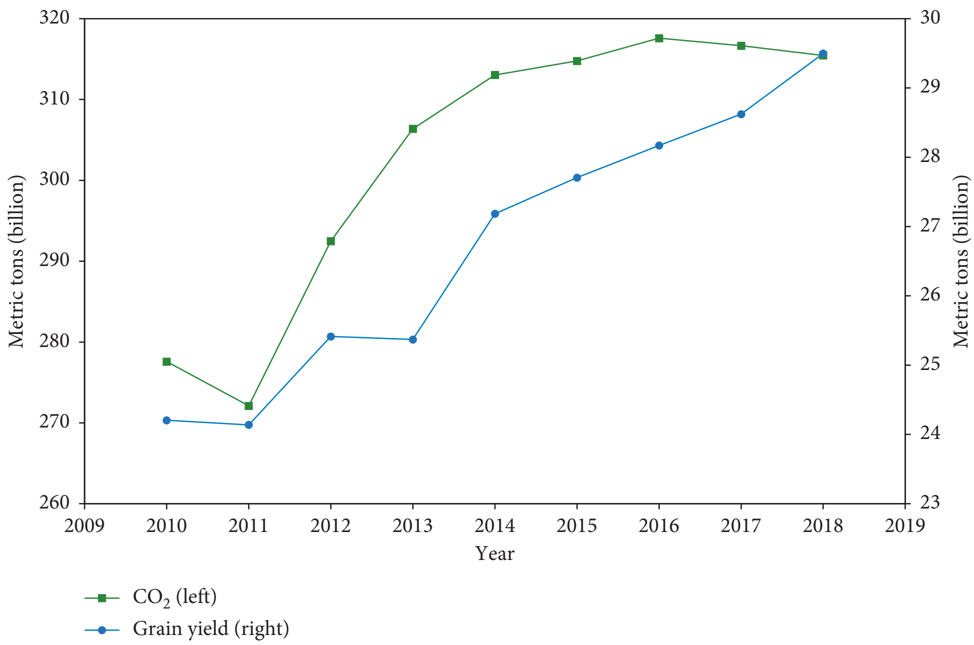

FIGURE 1: CO_2 emissions and grain production.

$$\left(P_{ij}\right)_{m\times n}=\begin{bmatrix} P_{11} & P_{12} & \cdots & P_{1n} \\ P_{21} & P_{22} & \cdots & P_{2n} \\ \cdots & \cdots & \cdots & \cdots \\ P_{m1} & P_{m2} & \cdots & P_{mn} \end{bmatrix}. \tag{2}$$

Then, we calculate the entropy of each indicator according to the formula as follows:

$$e_j=-k\sum_{i=1}^{n}p_{ij}\ln\left(p_{ij}\right),\quad k=\frac{1}{\ln n}. \tag{3}$$

We calculate the degree of difference (information utility value) of each indicator and set the difference coefficient as g_j which is given as follows:

$$g_j=1-e_j. \tag{4}$$

The weight of each indicator is as follows:

$$w_j=\frac{g_j}{\sum_{j=1}^{n}g_j}. \tag{5}$$

Therefore, the comprehensive score of each country can be obtained as follows:

$$s_i=\sum_{j=1}^{m}w_j\times p_{ij}. \tag{6}$$

Because the value of s_i is small and not easy to be directly observed, the following method is used to project it into the [0, 100] interval to construct the EPI (environmental pollution index) as follows:

$$\mathrm{EPI}=\frac{s_i-\mathrm{Min}\left(s_i\right)}{\mathrm{Max}\left(s_i\right)-\mathrm{Min}\left(s_i\right)}\times 100. \tag{7}$$

3.2. Results Analysis. According to the above steps, calculate the collected data and use MATLAB to calculate and obtain the index of the entropy and weight, for the future comprehensive score calculation. The results are shown in Table 1.

After determining the weight and the amount of information, the final comprehensive score of each country's environmental pollution level is obtained, which we call environmental pollution index (EPI), as shown in Table 2.

We use histogram and radar chart to show the score results; in the histogram of Figure 2, the higher the area, the higher the environmental pollution index and the more serious the agricultural pollution.

4. Grain Production Efficiency Model

4.1. DEA Model of SBM Super Efficiency. The DEA model is a special tool based on linear programming to evaluate the relative effectiveness of work performance of the same type of organizations. It can effectively eliminate the interference of external environment and random errors on efficiency calculation and can evaluate the world food production efficiency well. However, the pure DEA model can only take the expected output efficiency as the output index and cannot take the unexpected pollutants in the agricultural production process into account in the model [25–27]. Therefore, this paper will use the traditional DEA model based on the use of the SBM super efficiency model so that the DEA method can take into account the unexpected output in the calculation and can reduce the unexpected output from b_1 to b_2 and increase the expected output from g_1 to g_2 by reducing the input of the decision-making unit, as shown in Figure 3.

Table 1: Weight and entropy.

Indicators	Weight	Entropy
Agricultural irrigation	0.1309	0.8346
CO_2 emissions	0.1748	0.7793
Deforestation	0.3002	0.6208
Fertilizer consumption	0.3942	0.5021

Table 2: Score and ranking.

Rank	1	2	3	4	5	6	7	8	9	10
Country	IND	CHN	VNM	DEU	FRA	USA	BRA	CAN	RUS	ARG
EPI	100	61	43	30	26	17	7	4	1	0

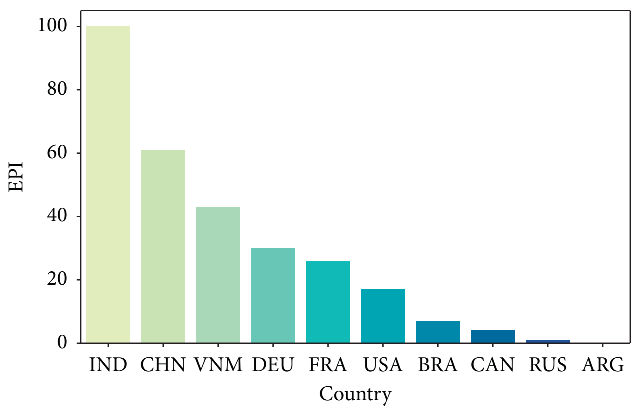

Figure 2: EPI histogram.

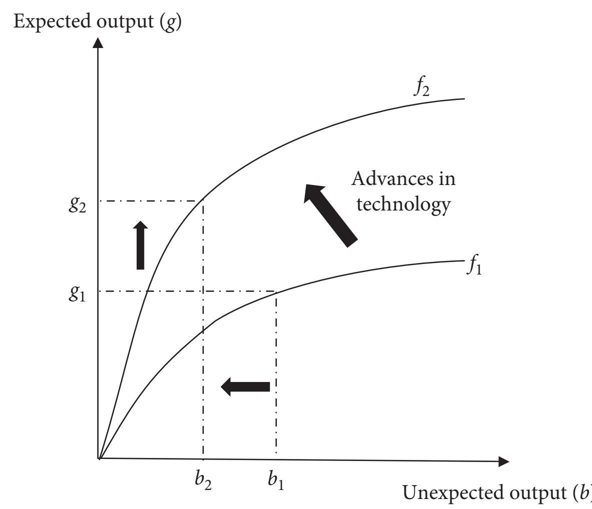

Figure 3: DEA method.

Assuming that a system has n decision-making units, m inputs, and s outputs, the input and output indicator vectors of the j DMU are as follows:

$$X_j = \left(x_{1j}, x_{2j}, \ldots, x_{mj}\right)^T > 0,\ Y_j = \left(y_{1j}, y_{2j}, \ldots, y_{sj}\right)^T > 0, \quad j = 1, 2, \ldots, n, \tag{8}$$

where $X_{ij}\,(i = 1, 2, \ldots, m)$ is the ith input variable of the jth DMU and $Y_{ij}\,(j = 1, 2, \ldots, s)$ is the rth output variable of the jth DMU. The VRS input-orientated DEA model is as follows:

$$\begin{cases} \min \quad \rho_{SE} = 1 + \dfrac{(1/m)\sum_{i=1}^{m} s_i^-}{x_{ik}} \\ \text{s.t.} \quad \displaystyle\sum_{j=1, j\neq k}^{n} x_{ij}\lambda_j - s_i^- \le x_{ik} \\ \qquad \displaystyle\sum_{j=1, j\neq k}^{n} y_{rj}\lambda_j \ge y_{rk}, \end{cases} \tag{9}$$

where $\lambda \ge 0, s^- \ge 0, s^+ \ge 0$; $i = 1, 2, \ldots, m$; $r = 1, 2, \ldots, q$; $j = 1, 2, \ldots, n\,(j \neq k)$; ρ_{SE} represents the efficiency value of the decision-making unit under the SBM super efficiency model; x_{ij} represents the total amount of input element i in country j; y_{rj} represents the total amount of type r output in country j; s^+ and s^- represent the relaxed variables of input and output vectors; and k represents the country on the effective production boundary.

Environmental efficiency is divided into natural disposable environmental efficiency and management disposable environmental efficiency. Natural disposability refers to reducing the corresponding unexpected output by reducing the input of the system; management disposability, contrary to natural disposability, refers to increasing the expected output of the system and reducing the unexpected output of the system by continuously improving the technical level and increasing the input of the system.

In order to describe the change of agricultural production efficiency over time, this paper uses data from different countries during 2010–2018 to construct the Malmquist production efficiency index [28] as follows:

$$M^t = \frac{D^t\left(x^{t+1}, y^{t+1}\right)}{D^t\left(x^t, y^t\right)}. \tag{10}$$

The efficiency change index can be further divided into pure technical efficiency change index and scale efficiency change index:

$$\begin{aligned} M\left(x^t, y^t, x^{t+1}, y^{t+1}\right) &= \left[\frac{D^t\left(x^{t+1}, y^{t+1}\right)}{D^t\left(x^t, y^t\right)} \times \frac{D^{t+1}\left(x^{t+1}, y^{t+1}\right)}{D^{t+1}\left(x^t, y^t\right)}\right]^{1/2} \\ &= \left[\frac{D_c^t\left(x^{t+1}, y^{t+1}\right)}{D_c^{t+1}\left(x^{t+1}, y^{t+1}\right)} \times \frac{D_c^t\left(x^t, y^t\right)}{D_c^{t+1}\left(x^t, y^t\right)}\right]^{1/2} \times \frac{D_c^{t+1}\left(x^{t+1}, y^{t+1}\right)}{D_c^t\left(x^t, y^t\right)} \\ &= \mathrm{TC}(\mathrm{CRS}) \times \mathrm{EC}(\mathrm{CRS}) \\ &= \mathrm{TC}(\mathrm{CRS}) \times \mathrm{PTEC}(\mathrm{VRS}) \times \mathrm{SEC}(\mathrm{VRS}, \mathrm{CRS}), \end{aligned} \tag{11}$$

where

$$\begin{aligned} \mathrm{PTEC}(\mathrm{VRS}) &= \frac{D_v^t\left(x^{t+1}, y^{t+1}\right)}{D_v^{t+1}\left(x^t, y^t\right)}, \\ \mathrm{SEC}(\mathrm{VRS}, \mathrm{CRS}) &= \frac{D_v^t\left(x^t, y^t\right)}{D_c^t\left(x^t, y^t\right)} \times \frac{D_c^{t+1}\left(x^{t+1}, y^{t+1}\right)}{D_v^{t+1}\left(x^{t+1}, y^{t+1}\right)}. \end{aligned} \tag{12}$$

4.2. Index Selection and Data Processing. In order to study the efficiency of the global food production system, we selected the top 10 countries in the global agricultural production scale in the past few years, namely: China, USA, India, Brazil, Russia, France, Canada, Vietnam, Germany, and Argentina. In this paper, each country is regarded as a decision-making unit (DMU). Therefore, there are a total of 10 DMUs. On the basis of reference to relevant research, we determined the indicators as shown in Table 3.

Output Indicators. The output indicators include expected output and unexpected output. The expected output is agricultural GDP, and the unexpected output is CO_2 emission.

Input Indicators. As the DEA model selected in this paper includes unexpected output indicators, not only labor force, agricultural arable land area, and agricultural irrigation area are selected for input indicators but also some indicators that will generate unexpected output but play a key role in food production, including agricultural machinery and fertilizer consumption.

4.3. Results Analysis. The analysis results with DEAP2.1 software are shown in Table 4. Without considering environmental factors and random factors, the average value of agricultural comprehensive technical efficiency, the average value of pure technical efficiency, and the average value of scale efficiency of various countries in 2018 were 0.368, 0.769, and 0.452, respectively. The maximum comprehensive technical efficiency is 1.000 (China and the United States), and there is room for improvement in other countries in all aspects; the minimum comprehensive technical efficiency is 0.059 (France).

By calculating the Malmquist average index from 2010 to 2018, it can be seen from Table 5 that the development of Vietnam started later, so the development speed in recent years is faster. The EFFCH (technical efficiency), scale efficiency (SECH), and total factor productivity (TFPCH) of the Malmquist average index are the highest, while there is still room for improvement in terms of technological progress. As an old agricultural exporter, Canada has the highest TECHCH and France has the highest PECH.

The Malmquist index from 2010 to 2018 was cluster analyzed by Python, and the corresponding spectrum cluster graph is obtained as shown in Figure 4. The cluster results of agricultural production efficiency of various countries in 9 years can be divided into 3 categories: Canada, Germany, and Russia in the first category; Brazil, China, Vietnam, India, and the United States in the second category; and the other 2 countries belong to the third category and are divided into Argentina and France, respectively.

5. Regression Analysis of Factors Affecting Production Efficiency

In order to find the influencing factors of production efficiency, this paper chooses to establish a regression model [29]. Because the minimum value of efficiency value is 0 and the result of the super efficiency model makes the efficiency value not limited to 1, there is no limitation in the selection of the regression model. In this paper, OLS and Tobit models are selected for analysis.

5.1. OLS Model. The five input factors of the DEA model are taken as independent variables, namely, Labor (X_1), Agricultural Land (X_2), Agricultural Irrigation (X_3), Fertilizer

Table 3: Indicator selection.

Input indicators	Output indicators	
	Expected output	Unexpected output
Labor (million) Agricultural land (percent of land area) Agricultural irrigation (percent of total agricultural land) Fertilizer consumption (kilograms per hectare of arable land) Agricultural machinery (tractors per 100 Sq. km of arable land)	Grain yield (billions of tons)	Environmental pollution index

Consumption (X_4), and Agricultural Machinery (X_5). The ecological efficiency value (Y) calculated by the DEA model is taken as dependent variable, and the following multiple linear regression model is constructed by taking logarithm on both sides, respectively:

$$\ln Y = \beta_0 + \beta_1 \ln X_1 + \beta_2 \ln X_2 + \beta_3 \ln X_3 + \beta_4 \ln X_4 + \beta_5 \ln X_5 + \mu. \tag{13}$$

Efficient β_0 is the intercept term, and regression coefficient β_i represents the percentage of the impact of changes in input factors on changes in ecological efficiency value, and μ is a random error term.

5.2. Tobit Model. The Tobit model, also known as sample selection model and restricted dependent variable model, refers to the value taking model when the explained variables are continuous but subject to certain restrictions, which is applicable to the cases where the explained variables have zero value and the remaining values are positive and continuous. In the estimation of the model, the potential explained variables Y^* satisfy the basic assumptions of the classic linear model and are subject to independent normal distribution of the same variance. The basic form of the model is as follows:

$$\begin{gathered} Y_t^* = a_t + \sum_{j=1}^{r} \beta_j X_{tj} + \varepsilon_t t = 1, 2, \ldots, n;\ j = 1, 2, \ldots, r, \\ Y_t^* = \begin{cases} Y_t^* & Y_t^* \geq 0 \\ 0 & Y_t^* \leq 0 \end{cases}, \end{gathered} \tag{14}$$

where $X = (x_1, x_2, \ldots, x_n)'$ is the vector of explanatory variables, that is, input of factors; $Y = (y_1, y_2, \ldots, y_n)'$ is the vector of explanatory variables, that is, the value of eco-economic efficiency of peasant households; $\beta = (\beta_1, \beta_2, \ldots, \beta_n)'$ is the parameter vector; and $\varepsilon = (\varepsilon_1, \varepsilon_2, \ldots, \varepsilon_n)'$ is the residual.

5.3. Results Analysis. From Table 6, it can be seen that the OLS and Tobit results are basically the same, and the regression coefficients of the explanatory variables X_2, X_3, and X_4 are all negative, indicating that the increase in agricultural arable land, agricultural irrigation, and fertilizer use will have an adverse impact on the efficiency of food production. The regression coefficients of X_1 and X_5 are positive, indicating that labor input and agricultural machinery use are directly proportional to their production efficiency.

6. Comprehensive Evaluation Model of Efficiency and Sustainability

In the weight of environmental pollution in Table 1, the weight of fertilizer use is the largest, and in the regression analysis in Table 6, fertilizer use also has good explanatory effect. In order to express the direct connection between agricultural production efficiency and sustainability, the amount of fertilizer used is selected to connect the sustainability and production efficiency of world food production. When the fertilizer usage is reduced in a linear way [30–34], we name it as the process of increasing the proportion coefficient. When the proportion coefficient is 0, it means to keep the original state. When the proportion coefficient is 1, it means not to use the fertilizer. Developing countries and developed countries are selected at different stages to substitute into the environmental pollution assessment model and obtain the change relationship between EPI and proportion coefficient as shown in Figure 5; the change relationship between comprehensive technical efficiency and proportion coefficient is shown in Figure 6.

With other indicators unchanged, the impact of reducing fertilizer use on different countries is calculated. In Figure 5, the EPI of each country shows the same downward trend with the decrease in fertilizer use. In Figure 6, with the decrease in the EPI, the comprehensive technical efficiency of China is in a decreasing stage. In Germany and India, the comprehensive technical efficiency is increasing.

If Figures 5 and 6 are drawn on the same graph, the direct relationship between agricultural production efficiency and sustainability can be obtained as shown in Figure 7. This indicates that some countries have invested too much fertilizer at present, resulting in the positive expected output efficiency lower than the unexpected output efficiency. Therefore, reducing the input of fertilizer can effectively improve the production efficiency and reduce environmental pollution.

Table 4: Returns to economies of scale in 2018.

Country	CHN	USA	IND	BRA	RUS	FRA	CAN	VNM	DEU	ARG	Mean
MALM	1	1	0.275	0.278	0.661	0.059	0.095	0.111	0.137	0.066	0.368
TECH	1	1	0.409	1	1	0.31	1	0.325	0.642	1	0.769
EFFI	1	1	0.673	0.278	0.661	0.189	0.095	0.342	0.214	0.066	0.452
Return on scale	—	—	IRS	IRS	IRS	IRS	IRS	IRS	IRS	IRS	—

Table 5: Average Malmquist index.

Country	CHN	USA	IND	BRA	RUS	FRA	CAN	VNM	DEU	ARG
EFFCH	0.970	1	1	1	0.928	1.037	1.017	1.057	0.875	1.004
TECHCH	1.003	0.982	0.972	0.99	0.993	0.973	1.006	0.958	1.001	0.989
PECH	1.006	1	1	1	1	1.007	1	1.004	1	1
SECH	0.964	1	1	1	0.928	1.03	1.017	1.054	0.875	1.004
TFPCH	0.973	0.982	0.972	0.99	0.922	1.009	1.023	1.013	0.876	0.994

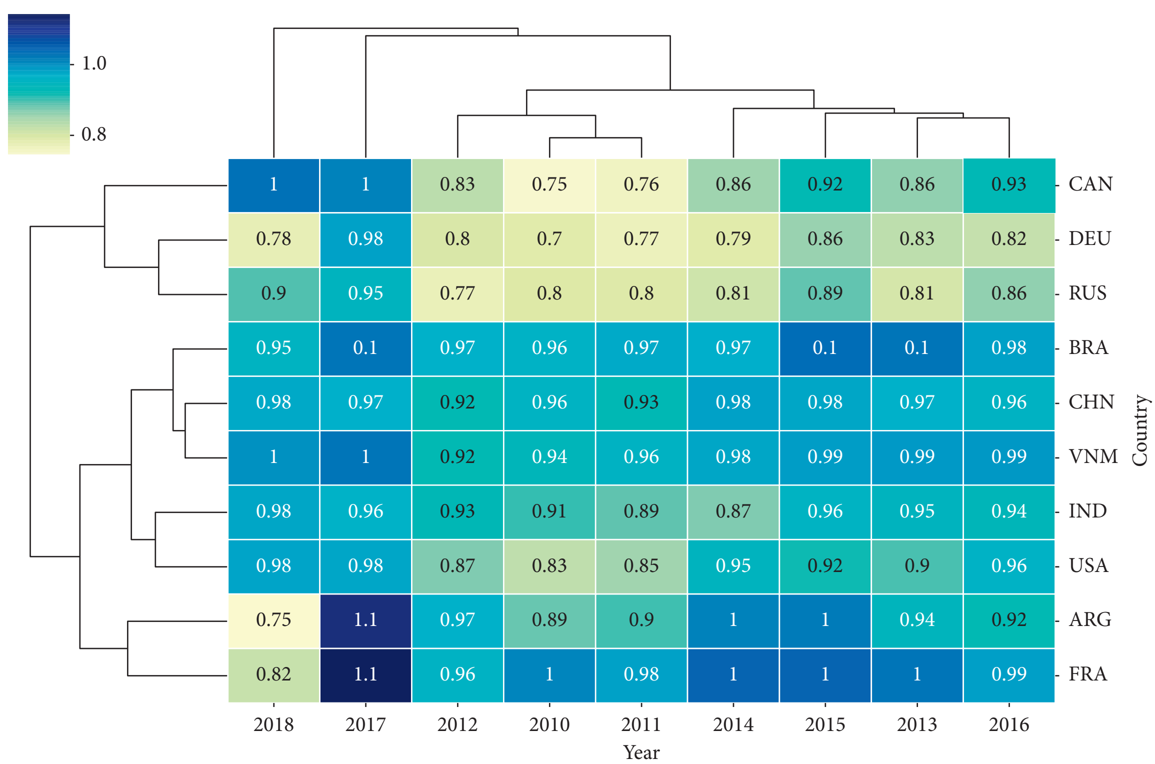

Figure 4: Cluster analysis of Malmquist index.

Table 6: Regression results of influencing factors.

Variable		C	X_1	X_2	X_3	X_4	X_5
OSL	Coefficient	−2.8272	0.6859	−0.0485	−0.1593	−0.2789	0.1784
	t-statistic	−2.2029	3.2117	−0.1692	−0.5691	−1.0489	0.6464
Tobit	Coefficient	0.3786	0.001	−0.002	−0.0044	−0.0003	0.0002
	z-statistic	2.408	2.6567	−0.4355	−0.486	−0.7838	0.5998

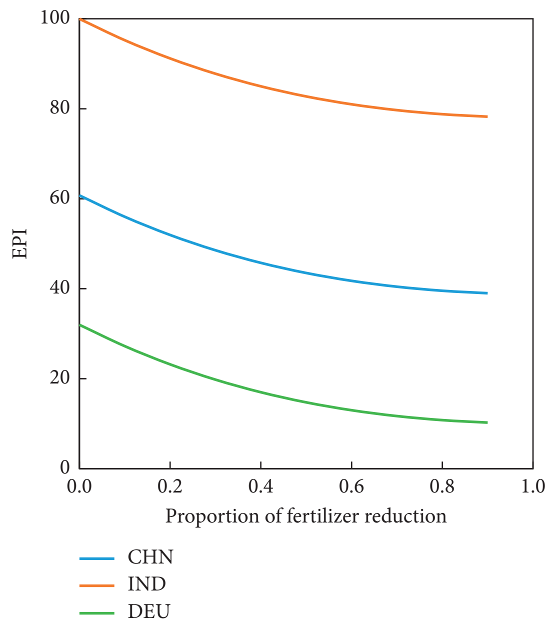

Figure 5: EPI changes.

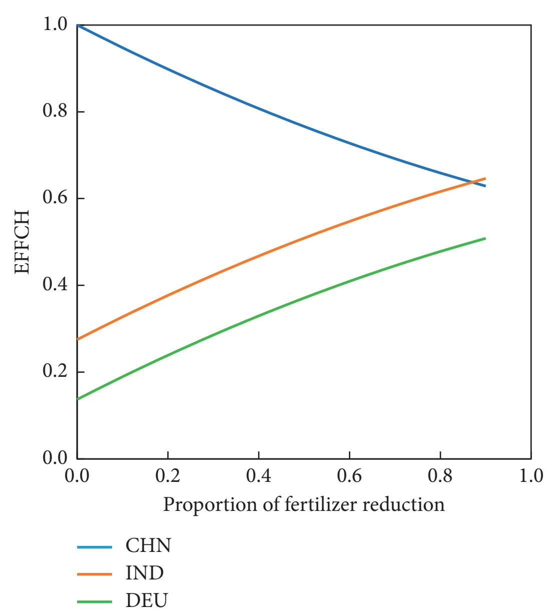

Figure 6: EFFCH changes.

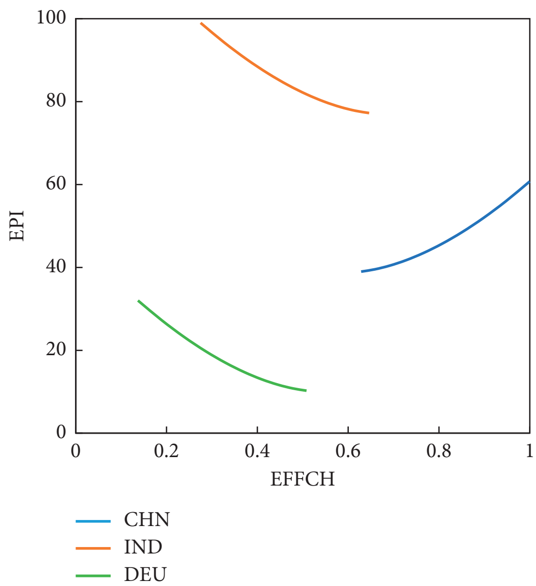

Figure 7: EFFCH-EPI.

7. Conclusion

(1) In this paper, 4 indicators of agricultural irrigation area, CO_2 emissions, deforestation area, and fertilizer use were selected, and the environmental pollution assessment model was established by using the method of entropy weight, and the environmental pollution index was obtained. Among the 10 major agricultural producing countries, India has the highest degree of environmental pollution, and Argentina has the lowest degree.

(2) Through the establishment of the DEA model, it is found that the countries with the highest comprehensive technical efficiency are China and the United States and Vietnam has the highest rate of technological progress. The subsequent regression analysis model indicates that the increase in agricultural arable land, agricultural irrigation, and fertilizer use will have an adverse impact on the economic efficiency value of food production, and the labor input and agricultural machinery use are directly proportional to their ecological economic efficiency value.

(3) The OSL and Tobit models were used to conduct regression analysis on the factors affecting the production efficiency, and the results showed that the increase in agricultural arable land, agricultural irrigation, and fertilizer use would have an adverse impact on the food production efficiency. The input of labor force and the use of agricultural machinery are directly proportional to their production efficiency.

(4) Combining the environmental pollution index with the comprehensive technical efficiency, the relationship between the two has been obtained through the control of fertilizer use. Some countries have invested excessive fertilizer in production, resulting in the positive expected output efficiency lower than the unexpected output efficiency. Reducing the input of fertilizer can effectively improve the production efficiency and reduce environmental pollution.

The research of this paper also has some deficiencies as follows:

(1) Due to the lack of data, the latest data can only be researched into 2018, and the changes in the last two years have not been considered.

(2) In this paper, only 10 countries are selected to represent the global agricultural production system, and the environmental pollution status of some countries with characteristic crops is not considered, which may be different from the main agricultural producing countries.

In conclusion, our research results can provide a theoretical basis for evaluating the efficiency of agricultural production and the health of environmental pollution system in a country and contribute to the reform of agricultural development so as to promote environmental protection and sustainable development of agriculture.

Data Availability

The data used to support the findings of this study are included within the article.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

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