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Retraction

Retracted: Analysis Method of Agricultural Total Factor Productivity Based on Stochastic Block Model (SBM) and Machine Learning

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This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

(1) Discrepancies in scope
(2) Discrepancies in the description of the research reported
(3) Discrepancies between the availability of data and the research described
(4) Inappropriate citations
(5) Incoherent, meaningless and/or irrelevant content included in the article
(6) Manipulated or compromised peer review

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

Wiley and Hindawi regrets that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our own Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

References

[1] Y. Li, C. Chen, F. Liu, and J. Wang, "Analysis Method of Agricultural Total Factor Productivity Based on Stochastic Block Model (SBM) and Machine Learning," *Journal of Food Quality*, vol. 2022, Article ID 9297205, 11 pages, 2022.

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Research Article

Analysis Method of Agricultural Total Factor Productivity Based on Stochastic Block Model (SBM) and Machine Learning

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When analyzing agriculture's total factor productivity, traditional measurement approaches do not take into account the inefficiency value. The production functions are assumed to be analyzed on basis of the random boundaries, which makes the analysis results inaccurate and unreliable. As a result, this paper proposes an analytical approach for agricultural total factor productivity based on the stochastic block model (SBM), which combines the benefits of statistics and machine learning. It uses the SBM direction distance function and the Luenberger productivity index to measure the agricultural efficiency, total factor productivity, and their components. The research study considers the data from 31 provinces from 2006 to 2018 years. First, one output indicator and six input indicators are established. The time-varying variations of the national agricultural inefficiency value and its source decomposition under variable scale returns are then determined using the SBM-based algorithm of agricultural total factor productivity and the obtained sample data. The changes of the agricultural total factor productivity and its components are comprehensively analyzed. Following an examination of the elements impacting agricultural efficiency and productivity, the socioeconomic development of the agricultural total factor productivity is examined in order to achieve efficient growth.

1. Introduction

Agriculture is the foundation of the national economy. Since the reform and opening up, the overall agricultural productivity has greatly improved in developing countries like China [1, 2]. In China, 9% of the world's arable land has been cultivated to feed 22% of the world's population, which makes an important contribution to the world food security [3]. However, despite the fact that China is a huge agricultural country, agriculture production remains inefficient on a global scale. Under the condition of rigid food demand growth, China's agricultural production is constrained by arable land and water resources [4, 5]. Per capita arable land is 40%, and per capita freshwater resources are less than 28% of the world's average resources [6]. China's agricultural infrastructure is relatively weak, and climate change has been unusual in recent years, adding to the productivity analysis uncertainty [7]. Agriculture productivity is the most vulnerable to climate change [8]. In addition, the external environment of China's agricultural development is constantly changing. After joining the WTO in 2005, agriculture was fully opened to the outside world. Since January 1, 2006, the United Nations World Food Programme has stopped food aid to China for 26 years. China's agricultural growth is under pressure from two directions: nationalist demands and agricultural product export requirements [9]. Under such situation, the promotion of the sustainable development of agriculture is imperative and it safeguards the food security as well.

Technology and productivity are associated for every nation's agriculture and economic growth, according to the notion of contemporary economic growth and production methods [10]. The overall improvement is the main driving force for the promotion of agricultural production capacity in the future [11, 12]. Moreover, it is necessary to improve the agricultural efficiency and the total factor productivity

[13] in order to achieve intensive production and solve the rural problems of the developing nations. Therefore, the research study performed in this article is particularly important.

The study on the measurement technique of grain production efficiency and the selection of indicators for grain production efficiency assessment are the two fundamental components of grain production efficiency measurement. The parametric technique, which is represented by the stochastic Frontier method (SFM), and the nonparametric method, which is represented by the data envelopment analysis method (DDA), are the most popular. The DEA has become the most extensively used approach for performance analysis, with benefits such as simultaneous treatment of various network input and nonparametric processing of effective limits. It is broadly applied in power, transport, finance, and other industries [14–16]. These methods are used by scholars in measurement of grain production efficiency [17]. The majority of researchers considered input elements such as land, water resources, labor, pesticides, and chemical fertilizers to be production factors [18]. The degree of urbanization, the degree of openness to the outside world, the prevalence of catastrophes, and nonrural job prospects are all external variables that have a substantial impact on grain output [19]. With the advancement of spatial econometrics and geosciences in recent years, an increasing number of researchers have begun to employ spatial econometric approaches to study production efficiency by integrating data points with their physical positions [20]. Although a few researchers have considered environmental factors when analyzing grain production efficiency, they have only looked at undesirable output (such as compound oxygen consumption, total nitrogen, and phosphorus (p) and have given little weight to carbon sequestration output resulting from grain production's societal benefits [21]. When analyzing the total factor productivity of agriculture, the inefficiency value and the relaxation variable are not considered by the traditional measurement model based on Cobb-Douglas (C-D) production function, and the function form needs to be assumed by analyzing the random boundary, which makes the analysis results error prone [12, 22]. Therefore, the analysis method of agricultural total factor productivity based on machine learning and SBM is proposed in the paper. The contribution of the research work is as follows:

SBM model is proposed to analyze the agricultural total factor productivity.

As a new measurement method, Luenberger productivity index is used, which makes up for the existing deficiencies in the agricultural productivity.

The contribution of livestock input, sown area, and personnel input is taken into consideration and comparative analysis is done for VRS and CRS method.

The rest of the paper is organized as follows: in Section 2, the proposed analysis methods of agricultural total factor productivity are discussed. In Section 3, SBM-based algorithm of agricultural total factor productivity is discussed. In Section 4, Luenberger productivity index is elaborated followed by empirical analysis in Section 5. Section 6 concludes the research work.

2. The Proposed Analysis Method of Agricultural Total Factor Productivity

Agriculture productivity forecasting is critical for determining if the present output can fulfil citizen needs, as well as determining the export and import quantities of agricultural goods based on predicted demand. The proposed model is defined in the block diagram as shown in Figure 1.

3. SBM-Based Algorithm of Agricultural Total Factor Productivity

To establish the best practice boundaries of China's agricultural output in each time, each province is employed as a production decision unit [15]. Each province uses N types of the inputs $x = (x^1, \ldots, x^n)$ to obtain the output $y = (y^1, \ldots, y^m)$. In period $t = 1, \ldots, T$, the input and output value of the $k = 1, \ldots, K$ province can be expressed as $(x^{k,t}, y^{k,t})$. Where the production feasibility set satisfies closed and bounded sets and the outputs and the inputs are freely distributable, the DEA can be used to model the production technology as shown in

$$p^t = \left\{ \left(x^t, y^t\right):\ x_n^t \geq \sum_{k=1}^{K} \lambda_k^t x_{nk}^t,\ \forall n;\ y_m^t \leq \sum_{k=1}^{K} \lambda_k^t y_{mk}^t,\ \forall m;\ \sum_{k=1}^{K} \lambda_k^t = 1, \lambda_k^t \geq o,\ \forall k \right\}, \tag{1}$$

where $x^t = (x_1^t, \ldots x_N^t)$; $y^t = (y_1^t, \ldots y_M^t)$. (x^t, y^t) indicates the input and output values for period t; x_n^t is n types of input during t; y_m^t is m types of output during period t; λ_k^t is the weight variable. The weighted sum is 1 and the nonnegative weighting constraint means variable returns to scale (VRS).

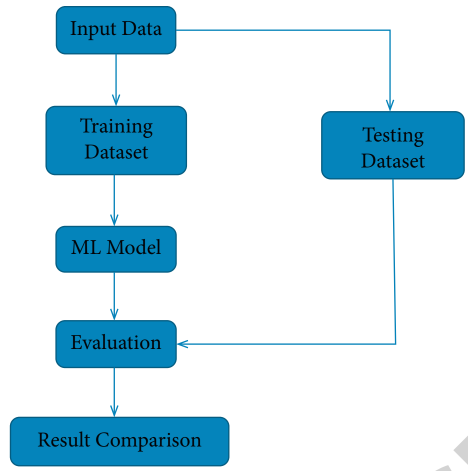

Figure 1: Block diagram for showing the proposed work for analyzing the agriculture productivity.

3.1. SBM Direction Distance Function. The SBM-based directional distance function $\overrightarrow{S}_V^t(x^{t,k\prime}, y^{t,k\prime}; g^x, g^y)$ is defined as in

$$\overrightarrow{S}_V^t\left(x^{t,k\prime}, y^{t,k\prime}; g^x, g^y\right) = \underset{s^x, s^y}{\text{Max}} \frac{\left(1/N \sum_{n=1}^{N} S_n^x / g_n^x\right) + \left(1/M \sum_{m=1}^{M} S_m^y / g_m^y\right)}{2}$$
$$\text{s.t.} \sum_{k=1}^{K} \lambda_k^t x_{kn}^t + s_n^x = x_{k'n}^t, \forall n; \sum_{k=1}^{K} \lambda_k^t y_{km}^t - s_m^y = y_{k'm}^t \forall m; \sum_{k=1}^{K} \lambda_k^t = 1, \lambda_k^t \geq 0, \forall k; s_n^x \geq 0, \forall n; s_m^y \geq 0, \forall m, \tag{2}$$

where $(x^{t,k\prime}, y^{t,k\prime})$ is the input and output vectors of the province $k\prime$ in the period t.

The (g^x, g^y) represents the positive direction vector for output expansion and input compression; (s_n^x, s_m^y) represents the relaxation vector; positive values of s_n^x and s_m^y represent the actual input which is greater than the boundary's value and the actual output is less than the boundary's value. When there is the same unit of measure for (g^x, g^y) and (s_n^x, s_m^y), the relaxation vector can be normalized, and then the normalized input relaxation and output relaxation can be separately added to find the average value. The objective function is to maximize the sum of the inefficient average of inputs and outputs.

Another advantage of using the function is that it can decompose inefficient sources and the inefficiencies can be broken down into the input inefficiency as shown in (3) and the output inefficiency as shown in (4):

Input inefficiency:

$$\text{IE}_x = \frac{1}{2N} \sum_{n=1}^{N} \frac{S_n^x}{g_n^x}. \tag{3}$$

Output inefficiency:

$$\text{IE}_y = \frac{1}{2M} \sum_{m=1}^{M} \frac{S_m^y}{g_m^y}. \tag{4}$$

4. Luenberger Productivity Index

The Malmquist index is used by many scholars for productivity studies, but it is based on radial and angular distance functions, which cannot consider the reduction of inputs and the increase of outputs simultaneously, and the variables must be changed in equal proportions. As a new measurement method, Luenberger productivity index [16] makes up for the existing deficiencies.

The Luenberger productivity indicator between t and $t+1$ period is defined in

$$\text{LTFP}_t^{t+1} = \frac{1}{2}\left\{\left[\overrightarrow{S}_C^t\left(x^t, y^t; g\right) - \overrightarrow{S}_C^t\left(x^{t+1}, y^{t+1}; g\right)\right] + \left[\overrightarrow{S}_C^{t+1}\left(x^t, y^t; g\right) - \overrightarrow{S}_C^{t+1}\left(x^{t+1}, y^{t+1}; g\right)\right]\right\}, \tag{5}$$

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where $[\vec{S}^{t}_{C}(x^t, y^t; g) - \vec{S}^{t}_{C}(x^{t+1}, y^{t+1}; g)]$ and $[\vec{S}^{t+1}_{C}(x^t, y^t; g) - \vec{S}^{t+1}_{C}(x^{t+1}, y^{t+1}; g)]$ represent the production indicators for the period t and the period $t+1$, respectively.

Similar Malmquist productivity indicators can be decomposed into technological advancements, pure efficiency changes, and scaled efficiency changes [17, 18]. Luenberger productivity index can be further decomposed into pure efficiency change as given in

$$\text{LTFP} = \text{LPEC} + \text{LPTP} + \text{LSEC} + \text{LTPSC}. \tag{6}$$

Pure technological progress is calculated as given in

$$\text{LPEC}_t^{t+1} = \vec{S}^{t}_{V}\left(x^t, y^t; g\right) - \vec{S}^{t+1}_{V}\left(x^{t+1}, y^{t+1}; g\right). \tag{7}$$

Scale efficiency change is given in

$$\text{LPTP}_t^{t+1} = \frac{1}{2}\left\{\left[\vec{S}^{t+1}_{V}\left(x^t, y^t; g\right) - \vec{S}^{t}_{V}\left(x^t, y^t; g\right)\right] + \left[\vec{S}^{t+1}_{V}\left(x^{t+1}, y^{t+1}; g\right) - \vec{S}^{t}_{V}\left(x^{t+1}, y^{t+1}; g\right)\right]\right\}. \tag{8}$$

Technological scale change is defined in

$$\text{LSEC}_t^{t+1} = \left[\vec{S}^{t}_{C}\left(x^t, y^t; g\right) - \vec{S}^{t}_{V}\left(x^t, y^t; g\right)\right] - \left[\vec{S}^{t+1}_{C}\left(x^{t+1}, y^{t+1}; g\right) - \vec{S}^{t+1}_{V}\left(x^{t+1}, y^{t+1}; g\right)\right], \tag{9}$$

$$\begin{aligned}\text{LTPSC}_t^{t+1} = \frac{1}{2}\Big\{&\left[\vec{S}^{t+1}_{C}\left(x^t, y^t; g\right) - \vec{S}^{t+1}_{C}\left(x^t, y^t; g\right)\right] - \left[\vec{S}^{t}_{C}\left(x^t, y^t; g\right) - \vec{S}^{t}_{V}\left(x^t, y^t; g\right)\right] \\ &+ \left[\vec{S}^{t+1}_{C}\left(x^{t+1}, y^{t+1}; g\right) - \vec{S}^{t+1}_{V}\left(x^{t+1}, y^{t+1}; g\right)\right] - \left[\vec{S}^{t}_{C}\left(x^{t+1}, y^{t+1}; g\right) - \vec{S}^{t}_{V}\left(x^{t+1}, y^{t+1}; g\right)\right]\Big\}.\end{aligned} \tag{10}$$

For each period of the index calculation, four linear programs need to be solved under the two assumptions of CRS (Constant Return to Scale) and VRS (Variable Return to Scale), respectively, so that eight SBM directional distance functions are obtained. The $\vec{S}^{t}_{C}(x^t, y^t, g^t)$, $\vec{S}^{t+1}_{C}(x^{t+1}, y^{t+1}, g^{t+1})$, $\vec{S}^{t}_{C}(x^{t+1}, y^{t+1}, g^{t+1})$, and $\vec{S}^{t+1}_{C}(x^t, y^t, g^t)$ represent the four SBM directional distance functions under the CRS hypothesis. The $\vec{S}^{t}_{C}(x^t, y^t, g^t)$ and $\vec{S}^{t+1}_{C}(x^{t+1}, y^{t+1}, g^{t+1})$ are the directional distance function in the same period, while the other two are intertemporal directional distance functions. When calculating the mixed directional distance function, there may be cases where the input and output value of period $t+1$ has no solution during period t. The method of sequence DEA (Data Envelopment Analysis) is used to reduce the number of solutions. According to the above method, agricultural efficiency and agricultural total factor productivity of China's 31 provinces from 2005 to 2020 are measured and machine learning is used to predict the further results based on these values.

5. Empirical Analysis

5.1. Data Processing. Select the total output value of agriculture, forestry, animal husbandry, and fishery (100 million Yuan) as the indicator of agricultural output. Employees in the first industry (ten thousand), total agricultural machinery power (ten thousand kilowatts), total crop sown area (thousands of hectares), chemical fertilizer use (ten thousand tons), effective irrigation area (thousands of hectares), and livestock (ten thousand tons) are input indicators. According to the proportion of the industry employees in Chongqing and Sichuan in year 2007, the input and output indicators of previous years were split.

Output indicator: this indicator uses the actual total output value of 2010.

Input indicators

(1) The first-industry employees mainly refer to the number of laborers engaged in agriculture, forestry, animal husbandry, fishery, and their subsectors.
(2) The total power of agricultural machinery mainly refers to the sum of mechanical power used in the above industries.
(3) The total sown area of crops can accurately reflect the situation of land investment in agricultural production.
(4) The amount of fertilizer used refers to the amount of nitrogen fertilizer, phosphate fertilizer, potash fertilizer, and compound fertilizer that are put into production.
(5) Effective irrigated area refers to the sum of the area of paddy fields and irrigated land that can be irrigated.
(6) Livestock is mainly used for sowing, arable land, and transportation.

Table 1 is the characteristic description of the resulting data. Both the agricultural labor force and the livestock input have experienced a greater degree of decline, with the largest decline in the eastern region. The area planted in the central and western regions has increased, while the sown area in the

Table 1: Average growth rate of each variable in 2006–2018.

	National average	Eastern average	Central mean	Western average
Labor input	−0.1021	−0.1479	−0.0405	−0.1067
Mechanical input	1.3226	0.5898	1.8004	1.6645
Seeded area	0.0057	−0.1585	0.1135	0.0817
Fertilizer	0.5474	0.3402	0.6447	0.6749
Effective irrigation area	0.2452	0.0679	0.4148	0.2838
Draught animal input	−0.5287	−0.6749	−0.5527	−0.3629
Total output of agriculture, forestry, and animal husbandry	2.1102	1.7069	2.3617	2.3087

eastern region has decreased. With the development of agriculture, the input of machinery and chemical fertilizers has increased substantially, and the effective irrigation area has also greatly increased. The improvement of agricultural production conditions and the increase of input factors have also led to the significant increase in agricultural output. Figure 2 shows the growth rate from year 2006–2018.

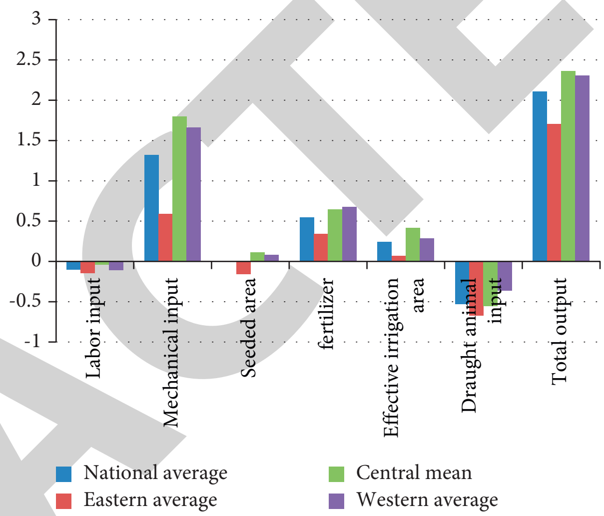

Figure 2: Growth rate from year 2006–2018.

5.2. Analysis of Empirical Results. Through the above data, the best production frontier of agriculture is constructed and the efficiency of agricultural production in each province is compared so as to clearly analyze the level of production efficiency and the gap between them. Each year's agricultural efficiency, total productivity factor, and their components are calculated to analyze the dynamic changes in each province. The three regions were divided to find out the difference between their development models.

5.2.1. Agricultural Efficiency and Its Decomposition. Set $g = (x, y)$; that is, the agricultural input and output observations as direction vectors. By using (2), agricultural inefficiency values are obtained. Different from the traditional distance function, the efficiency value obtained refers to the level of inefficiency based on slack variables. The large efficiency value represents the high level of inefficiency, that is, the long distance from the production frontier. If the value is zero, it indicates that the province is at the most efficient production frontier. The agricultural inefficiencies under the two assumptions of CRS and VRS were calculated and their sources were decomposed. From Table 2, it is seen that the two kinds of assumptions have different results. When results are different, the VRS-based results are chosen. Subsequent analysis of agricultural inefficiency was mainly based on the results of VRS.

From Table 2, it is found that the average value of the national agricultural inefficiencies under the VRS from 2005 to 2018 was 0.293. If the interpretation is based on the same proportion of variables, it means that each province should reduce its input by 29.3% and increase output by 29.3% to achieve full efficiency of agricultural production. However, in the case of using the SBM directional distance function, the number of employees in the primary industry decreased by 1.4%, the total mechanical power decreased by 1.5%, the planting area decreased by 2.4%, fertilizer use decreased by

Table 2: 2006–2018 China's regional average agricultural inefficiency and its source decomposition.

	CRS			
	National average	Eastern average	Central mean	Western average
IE	0.537	0.245	0.703	0.693
IE_L	0.023	0.013	0.021	0.035
IE_M	0.013	0.016	0.011	0.012
IE_S	0.021	0.007	0.029	0.029
IE_F	0.007	0.008	0.009	0.004
IE_I	0.006	0.003	0.004	0.010
IE_A	0.047	0.041	0.049	0.051
IE_Y	0.419	0.156	0.579	0.551
	VRS			
	National average	Eastern average	Central mean	Western average
IE	0.293	0.051	0.340	0.496
IE_L	0.014	0.001	0.014	0.026
IE_M	0.015	0.010	0.025	0.013
IE_S	0.024	0.003	0.038	0.033
IE_F	0.005	0.002	0.010	0.003
IE_I	0.017	0.005	0.029	0.019
IE_A	0.030	0.012	0.036	0.044
IE_Y	0.187	0.017	0.189	0.356

Note. A represents livestock input; Y represents total output of agriculture, forestry, animal husbandry, and fishery.

0.5%, the effective irrigation area decreased by 1.7%, the livestock input decreased by 3.0%, and the total output increased by 18.7%. The full efficiency of agricultural production is achieved. In the inefficiency of agricultural production, the total output contributed the most, at 63.98%. Agricultural resources are being seized by high-speed growth in the industry, which has led to investment and high-quality labor flows to the industrial sector. This leads to the reduction in the efficiency of agricultural production and the lack of total output [19]. The contribution of livestock inputs accounted for 10.41%, and the contribution of sown area accounted for 8.17%, while the contribution of other areas was relatively small.

From the regional point of view, the agricultural inefficiencies in the western and central regions were 0.496 and 0.340, respectively, while the inefficiency in the eastern regions was only 0.051. In terms of contribution, underproduction is the main source of inefficiency. In the western areas, the contribution of livestock input, sown area, and personnel input is greater; in the central ones, livestock input, sown area, and effective irrigation area contribute more. While in the eastern areas, the contribution is greater for livestock input and mechanical investment. The input of livestock is the inefficient common source in all regions. This shows that the use of livestock has hindered the improvement of production efficiency. The large proportion of machinery investment in the eastern areas may be due to the wealth of the region and the excessive investment in machinery. The land in the eastern regions is relatively flat and suitable for large-scale investment in machinery. In addition, it has sufficient funds to modernize agriculture, which is bound to increase investment in modern equipment. Excessive mechanical substitution can also result in inefficiency.

The inefficiency of the sown area was ranked third. In the central and western province, the inefficiency of the sown area was much higher than that of the eastern region, which contributed 3.8% and 3.3%, respectively. This may be related to the fragmentation of the arable land and the low degree of marketization. Fragmentation of arable land will result in loss of efficiency. In regions with higher degree of marketization, the efficiency of peasant households is also high. In contrast, the input inefficiency of practitioners in the central and western areas is larger, which can be seen from the average of the higher agricultural practitioners in the region. Through the decomposition of agriculture inefficiency, it is possible to clearly understand the absolute and relative differences in the level of agricultural efficiency between provinces and regions. Therefore, targeted policies were formulated to increase agricultural efficiency.

From the perspective of provinces, Shanghai, Jiangsu, Zhejiang, Shandong, and Hainan are on the boundary of agricultural production efficiency each year. Other provinces are not on the border. The agricultural efficiency of Beijing and Guangdong is only inferior to the above five provinces, and the distance from the boundary of agricultural production efficiency is very small. From the results, it can be seen that the provinces with higher agricultural efficiency are concentrated in the east. The provinces with low agricultural production efficiency include Ningxia, Shanxi, Gansu, Shaanxi, Qinghai, Guizhou, and Yunnan. In addition to Shanxi, the rest are western provinces. The facts above indicate that the eastern part of the economy is relatively developed; its investment in agricultural infrastructure, agricultural technology, and water conservancy has been highly effective; and the mastery and application of agricultural technology tend to be skilled, so the efficiency is higher [20].

From Table 3, it can be seen that from 2006 to 2012, the level of inefficiency in China's agriculture has increased year by year. Since 2004, the inflation, the market constraints, and the structural contradictions in agricultural development lead to difficulties in selling grain and increasing production but not increasing income, which seriously affect the enthusiasm of agricultural production. Therefore, more and more labor and capital is transferred from agriculture to industry and tertiary industry, which leads to the decline in agricultural efficiency year by year. The decline of agricultural development attracted the attention of the central government. Since 2013, the state has increased its support for agricultural production and has introduced a series of policies to support agriculture and benefit agriculture, especially rural tax and fee reform, which significantly increase the enthusiasm for production. The deterioration of agricultural production efficiency is contained, but there is still a large loss of efficiency in agricultural production.

5.2.2. Agricultural Total Factor Productivity and Its Decomposition. Agricultural total factor productivity is the dynamic analysis. It not only measures the relative position changes of agricultural production and specific production frontiers over a period of time, but also measures the movement of production frontiers over time.

Table 4 shows that from 2006 to 2018, the national total agricultural factor productivity was 5.88%, of which technological progress contributed the most, which was 4.03%, followed by the change in the technological scale, which was 1.41%. The other contributions were very small, 0.08% and 0.66%, respectively. This shows that its growth mainly comes from technological progress.

The productivity of the three regions has improved. The productivity in the eastern regions is the highest, followed by the central and the lowest in the western. From 2006 to 2018, the purely technical efficiency change in the west was a negative value of −1.53%. The efficiency in the eastern and central regions increased, but the improvement rate was relatively small, which was 0.98% and 0.88%, respectively. In contrast, technological progress in the regions is large, and the largest technological advancement is in the western region. The western region has the lowest agricultural efficiency due to less technological advancement.

Huge technological advancement will cause the big shift in the frontier of production. The distance between the actual production and the frontier of production will increase; at the same time, this will cause farmers to become unfamiliar with new technologies and cause the drop in efficiency. The scale efficiency in the eastern regions is the

Table 3: 2006–2012 annual agricultural null value and its source decomposition.

	2006	2007	2008	2009	2010	2011	2012
IE	0.259	0.271	0.289	0.318	0.327	0.326	0.330
IE_L	0.018	0.013	0.014	0.013	0.013	0.013	0.013
IE_M	0.014	0.015	0.015	0.018	0.015	0.016	0.012
IE_S	0.022	0.023	0.023	0.023	0.023	0.023	0.026
IE_F	0.005	0.007	0.005	0.004	0.003	0.004	0.003
IE_I	0.017	0.019	0.018	0.019	0.018	0.017	0.018
IE_A	0.032	0.029	0.031	0.028	0.030	0.033	0.033
IE_Y	0.151	0.164	0.184	0.213	0.225	0.220	0.223
	2003	2004	2005	2006	2007	2008	
IE	0.306	0.279	0.285	0.496	0.281	0.224	
IE_L	0.015	0.014	0.014	0.014	0.015	0.011	
IE_M	0.015	0.016	0.015	0.017	0.017	0.013	
IE_S	0.028	0.026	0.027	0.026	0.023	0.018	
IE_F	0.004	0.005	0.005	0.006	0.005	0.005	
IE_I	0.020	0.018	0.018	0.018	0.014	0.008	
IE_A	0..35	0.032	0.031	0.028	0.027	0.026	
IE_Y	0.189	0.168	0.175	0.180	0.179	0.163	

Table 4: Average growth rate of total factor productivity and composition of the whole country and regions from 2006 to 2018.

	National average	Eastern average	Central mean	Western average
LTFP	0.0558	0.0701	0.0591	0.0390
LPEC	0.0006	0.0098	0.0088	−0.0153
LPTP	0.0403	0.0398	0.0348	0.0452
LSEC	0.0008	0.0115	0.0040	−0.0124
LTPSC	0.0141	0.0089	0.0115	0.0215

highest, followed by the central, while in the western areas it is negative. The increase in productivity and scale efficiency of the eastern regions was mainly due to technological progress. The increase in the central and western areas was mainly due to technological advances and changes in technological scale. It can be seen that the regions in China have different characteristics of agricultural production. The scale of agricultural production in the eastern areas is more conducive to the improvement of productivity, while the others should learn from the development experience in the eastern areas and appropriately expand the scale of agricultural production [20, 21]. The difference in the scale of technology indicates that the eastern agricultural infrastructure and water conditions have reached a certain height. Due to the large space for improvement of production conditions and the western development policy, the scale of agricultural technology in the western regions has greater improvement.

In order to further examine the differences in the total factor productivity of the provinces, the standard deviation was used to test σ convergence. As shown in Figure 3, although the value of σ declined during part of the time, there is no σ convergence in China's agricultural productivity as a whole. The σ-values between 2006–2011 and 2013–2016 changed little and were relatively stable, but suddenly increased in 2012 and 2018. This shows that total factor productivity has the strong divergence during this period of time. During the period, the pure technical efficiency of 16 provinces deteriorated. In contrast, almost all provinces have advanced their technologies. The empirical results also show that the phenomenon of scale efficiency deterioration is mainly concentrated in the central and western regions, while the scale efficiency of most provinces in the eastern areas is increasing as seen in Figure 4.

It can be seen from Figure 4 that the fluctuation of China's agricultural total factor productivity is relatively obvious, and this fluctuation is basically consistent with the actual situation. Agriculture is most vulnerable to the impact of the climate. The catastrophic floods in 2008 severely affected China's agricultural production and caused the decline in total factor productivity, and then the difficulties in selling grain further undermined the enthusiasm of agricultural production which led to the decline of China's agricultural total factor productivity in the following four years. At the beginning of the 21st century, the issue of "producing peasants" was raised, which raised people's attention to agriculture. The impacts of a succession of steps adopted by the country, such as increasing the degree of anticomplementation of agriculture and lowering or exempting agricultural taxes, eventually became apparent and productivity increased again [13].

After China's accession to the WTO, the protection of agricultural products ended. In the face of fierce international competition, productivity has declined slightly. In 2018, it experienced the downward trend again, which may have certain relationship with the financial crisis. The demand and prices of food was hit by the financial crisis and the enthusiasm of farmers was affected. The trend and extent

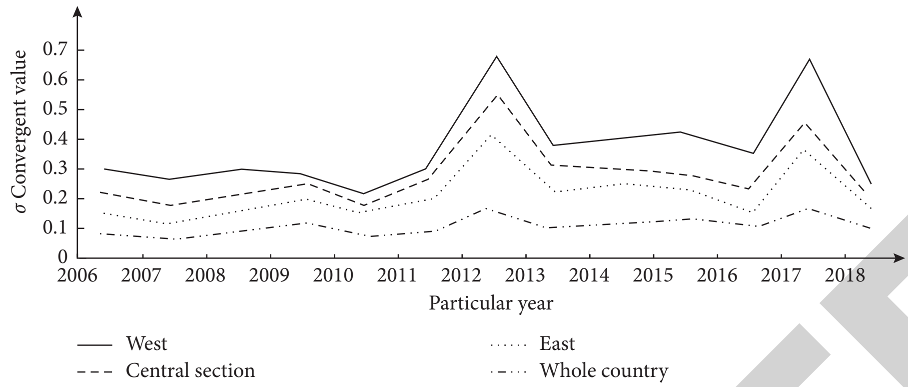

Figure 3: σ value of total factor productivity of agriculture in the whole country and the eastern, central, and western regions.

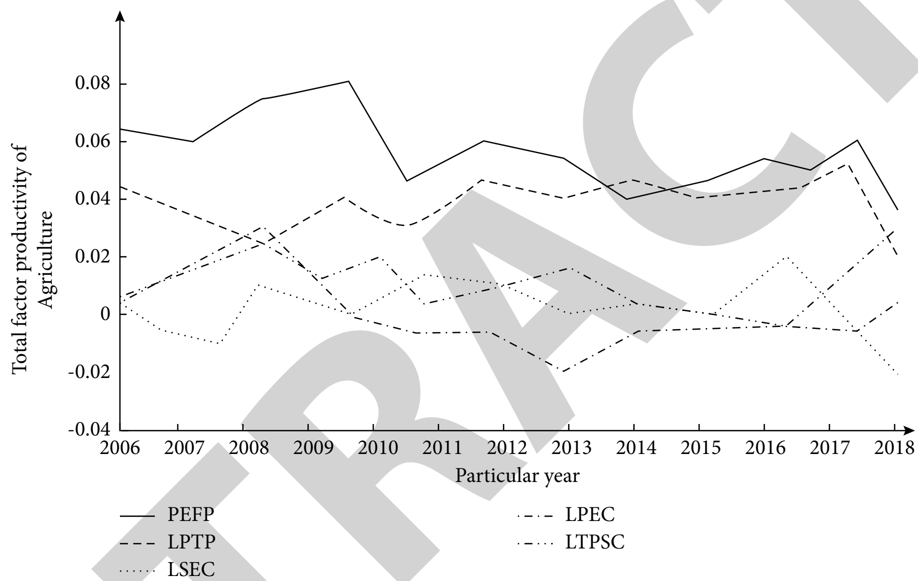

Figure 4: Temporal variation of agricultural total factor productivity and its components from 2006 to 2018.

of changes in technological progress and total factor productivity are relatively close; that is, the changes in total factor productivity are mainly caused by technological progress. Technical efficiency is declining in fluctuations. The use of existing technologies should be strengthened to promote the improvement of agricultural efficiency. Scale efficiency and technology scale fluctuate during the study.

5.3. Analysis of Factors Affecting Agricultural Efficiency and Agricultural Total Factor Productivity. The selection of factors is limited by the availability of data. The following influencing factors are mainly considered in this paper.

5.3.1. Structural Characteristics of Agricultural Production. The three indicators of the proportion of agriculture, machinery density, and animal husbandry in each province are used to express their production characteristics [17]. The importance of agriculture will affect the government's attitude toward agriculture. If agricultural output accounts for a large proportion of GRP, the labor and capital investment in production will be relatively large, and the production methods will also be different. This will have certain impact on efficiency and total factor productivity. Mechanization plays an important role in improving farmers' production conditions and increasing agricultural productivity. Animal husbandry is second only to crop production and occupies the important position in agricultural production, but its production method is different from that of crop production. In areas where animal husbandry and food are the major factors, it is worth considering whether there are differences in agricultural efficiency and total factor productivity.

5.3.2. Regional Characteristics. The proportion of the province's industries is used to express their industrial structure characteristics, and the proportion of the rural population in each province is used to represent the demographic characteristics. The development of industry will have impact on agricultural production. On the other hand, developed industries will provide beneficial technological spillovers and better infrastructure for agriculture. Excessive industrial projects may also be detrimental to agriculture. For example, the emission of wastes will destroy the production environment, and the development of industry will also compete with the agricultural sector for land, labor, and capital. Rural population has close relationship with agricultural efficiency and productivity. More rural population means that the efficiency of agricultural production is relatively low.

5.3.3. Fiscal Policy. Through the analysis of the proportion of the province's agricultural fiscal expenditures to its total fiscal expenditures, the study of agricultural efficiency and total factor productivity is affected by fiscal policy. The government's investment in agriculture is related to the development of agricultural technology and infrastructure construction, thereby affecting the efficiency and productivity of agricultural production. This proportion can fully reflect the status and weight of agriculture relative to other industries.

5.3.4. Education. The proportion of people with high school education and above is used to study the impact of education level (JYCD) on agricultural production. Human capital has the significant positive effect on rural output, but the loss of human capital in rural areas in China is serious, which disrupts the "spillover effect" of education on agriculture [18].

The relationship between agricultural efficiency and its influencing factors was analyzed using the Tobit model, while the relationship between agricultural total factor productivity and its influencing factors was analyzed by using regressions on panel data. Table 5 shows the analysis of determinants of agricultural efficiency and total factor productivity of agriculture.

Hausman test shows that the fixed effect model should be selected for the regression of agricultural total factor productivity. Based on the two assumptions of CRS and VRS, the influence of various factors on agricultural efficiency is consistent. From the above analysis, it can be seen that the proportion of agriculture in each province has negative effects on efficiency and productivity. Its impact on efficiency is significant, while the impact on productivity is not significant. This is inconsistent with the research of Fang Fuqian and Zhang Yanli. They concluded that if the agriculture is relatively important in the local economy, it will bring about increase in the TFP of agriculture.

The difference in research may be due to the differences in the object and time of the study. The large proportion of agricultural output to its GRP indicates that the area invested more labor and capital in agriculture. The growth of output may be extensive growth rather than the intensive increase in the improving of technology and efficiency. Mechanical density has significant negative effect on efficiency, which is consistent with Monchuk's findings. He found that areas with high levels of mechanization had low productivity and that they had positive relationship with productivity. The different effects on the two can be explained by the meaning of efficiency and productivity. The main difference between the two is that total factor productivity includes technological progress, while efficiency is only the application of existing technologies. The proportion of livestock husbandry is negative to them, which means that the larger the proportion of livestock husbandry is, the lower it is. This conclusion is consistent with Monchuk.

Regions with the large share of industrial output have low efficiency and productivity. Its effect on productivity is significantly negative, and the effect on efficiency is negative but not significant. Developed industries have negative externalities to agricultural production. The proportion of rural population is negatively correlated with them, and it is not significant. The higher the proportion of rural employees is, the greater their negative impact on agricultural TFP is. Agricultural productivity is increased by attracting part of the labor force to engage in nonagricultural production.

5.4. Agricultural Total Factor Productivity Leads the Development of Social Economy. In the 2015 government work report, "Improving Total Factor Productivity" was proposed by Prime Minister Li Keqiang as the important measure for stabilizing growth and restructuring [19]. The concept of "total factor productivity" was first proposed by the American economist Robert M. Solow, which reflects the production efficiency in a period of time. It means that economic growth cannot be attributed to tangible factors of production, but also includes technology and innovation.

In the past, the promotion of "labor productivity" was emphasized, and in 2015, the increase of the total factor productivity was first proposed. This is requirement that is proposed to meet the new normal of economic development. Judging from the supply of factors, China is facing the emergence of the Lewis turning point. Only by looking for dividends in institutional construction, technological innovation and reform can the opportunities for economic development be grasped, and the quality and effectiveness of economic growth can be improved.

On the one hand, improving total factor productivity can ease the pain of structural adjustment. It is necessary to transform the traditional industries through the improvement of total factor productivity and reduce the shock caused by the compression of excess production capacity. With the help of them, the competitive highlands of emerging industries were built to make up for the gaps caused by shutting down backward production capacity. On the other hand, improving total factor productivity can solidify the foundation for steady growth. As economic development enters the new normal, potential growth rates continue to decline. The downward pressure on the economy continues to increase this year, and the traditional economic growth momentum is weakening [20]. For this reason, the foundation of economic growth is stabilized by increasing total factor productivity.

To increase total factor productivity and lead the new normal of economic development, it is necessary to promote the innovation of organization, technology, and personnel training mechanisms.

Table 5: Analysis of determinants of agricultural efficiency and total factor productivity of agriculture.

	Agricultural efficiency				Total factor productivity of agriculture	
	VRS		CRS			
	Coefficient	*Z*-stat	Coefficient	*Z*-stat	Coefficient	*T*-stat
Intercept	1.0408	7.4152*	1.5132	14.2378*	0.2071	0.7182
Agricultural proportion	−0.0028	−1.2480	−0.0095	−5.5214	−0.0113	−2.3773**
Mechanical density	−0.0387	−4.5560*	−0.0319	−4.9716*	0.1848	6.5973*
Proportion of animal husbandry	−0.2486	−2.0152**	−0.1176	−1.2703*	−0.0152	−0.0423
Industrial proportion	−0.0027	−1.3278	−0.0138	−9.3029*	−0.0091	−1.9719**
The proportion of rural population	−0.0002	−0.3168	−0.0008	−1.5239*	−0.0020	−0.74.3
Government fiscal policy	−1.6756	−4.4787*	−1.2777	−4.8288*	−0.8814	−1.6323**
Educational level	0.0202	7.8719*	0.0132	7.1940*	0.0340	6.4282*
R^2 (scale)	0.1043	19.5853	0.1382	25.7347	0.7462	
Observation value	403		403		403	

Note. * indicates that the estimated coefficient is significant at the 1% level; ** indicates that the estimated coefficient is significant at the 5% level; *** indicates that the estimated coefficient is significant at the 10% level; and Scale is the scale parameter of the Tobit regression.

(1) It is necessary to deepen reforms so that the market plays the decisive role in the allocation of factors and promotes the innovation of organizations and production methods. The external factors that affect organizational innovation are market changes, especially changes in market competition. Fierce competition will enable the organization to innovate in order to obtain advantages. The principle of production mode innovation is to be guided by market demand. For this reason, the direct allocation of the production factors by the government should be greatly reduced through simple administrative devolution; the optimization of the allocation of production factors should be promoted through reforms.

(2) Innovation-driven strategies are implemented to promote technological progress. Technological progress is the direct driving force for improving total factor productivity. Its source comes from innovation. The implementation of this strategy should be based on the establishment of fair and competitive environment, the establishment of market-oriented mechanism, the strengthening of innovative functions, the improvement of incentive mechanisms, and the construction of scientific research system, and then improving the guidance-oriented evaluation system in the calculation of gross value of production and the performance assessment of state-owned enterprises is focused on.

(3) Talent is the key to improving total factor productivity. Innovative talents are trained and established through ways to improve education, enrich knowledge, and train new technologies.

6. Conclusion

In order to solve the drawbacks of the traditional measurement model based on C-D production function of statistics in the analysis of total factor productivity of agriculture, the analysis method based on SBM is proposed in this paper. Based on the SBM-based agricultural total factor productivity algorithm and the obtained sample data, the agricultural efficiency, agricultural total factor productivity, and its components in 31 provinces from 2006 to 2018 were analyzed. It is found that the average value of the national agricultural inefficiencies under the VRS from 2005 to 2018 was 0.293 and can be increased by technological advancement. The proposed method can certainly assist in bringing the revolutionary changes by analyzing the agriculture productivity from the past data and by predicting the factors influencing the overall production for the future. The production analysis will help in ascertaining how much yield would be enough for serving the people of own nation and how much can be exported to other nations using the SBM model.

Data Availability

The data will be made available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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