Environmentally-adjusted Analysis of Total Factor Productivity of Chinese Agriculture

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Abstract: By calculating the changes of agricultural total factor productivity in 31 provinces of China from 2007 to 2016 and analyzing its characteristics in time and space, it is found that the average annual growth rate of agricultural TFP in China during the sample period is 6.98%, and the dominant factor is technological progress rather than technological efficiency change. Good; pure technological efficiency and scale efficiency alternate in positive growth and negative growth. In terms of spatial characteristics, considering environmental factors, the changes of TFP, technological progress and technological efficiency in the central and western regions are significantly better than those in the eastern regions, and the three regions have convergence in terms of TFP, technological progress and technological efficiency.

1. Introduction

Spatial and temporal characteristics of agricultural production include temporal and spatial characteristics. The temporal characteristics are vertical analysis, referring to the change characteristics of agricultural production with time. The spatial characteristics are horizontal analysis, mainly referring to its distribution in different regions [1]. Scholars have studied this change for a long time by describing the patterns and processes of spatial and temporal scales of human migration, transportation, environmental change and socio-economic dynamics [2]. The study on the temporal and spatial changes of agricultural production is of great practical significance for establishing an effective allocation of production resources and a competitive agricultural production layout, promoting sustainable agricultural development, maintaining the balance between supplies.

China's agricultural sector has more than 300 million farmers, supporting more than 20% of the world's population, accounting for only 8% of the world's sown area, and accounting for 18% of the world's total grain production [3]. The temporal and spatial changes of agricultural production in China include not only the direct changes of agricultural production and operation, such as agricultural planting area [4], grain output [5] agricultural production waste [6]. It is of great practical significance to study the total factor productivity of agriculture in China. Whether the high growth is driven by factor input or by technological progress and efficiency improvement is a question worth studying.

With the rapid development of agricultural production and operation in China, Environmental factors have become the factors we must consider when we study and analyze agricultural growth and change. Under the dual constraints of resources and environment, how to calculate agricultural total factor productivity (TFP) scientifically and objectively, and how the total factor productivity of agriculture in China changes in time and space under environmental factors, and what characteristics it has, are of great significance to promote the green and sustainable development of agriculture in China. In this paper, using the method of combining MALMQUIST index with DEA model, the agricultural COD emissions (10,000 tons) and agricultural nitrogen and ammonia emissions (10,000 tons) are taken into account as unexpected outputs. The changes of agricultural total factor

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productivity in 31 provinces of China from 2007 to 2016 are calculated by input method, and their temporal and spatial characteristics are analyzed. Our research can provide policy reference for the sustainable development of agriculture in China.

2. Model Construction and Data Processing

2.1 Construction of MALMQUIST-DEA Model

Data Envelopment Analysis (DEA), proposed by Charnes and Cooper in 1978. Under the assumption of constant returns to scale, Charnes, Cooper and Rhodes proposed the CCR model in 1978, to measure the technical efficiency, allocation efficiency and cost efficiency of sample institutions. Subsequently, Banker, Charnes and Cooper proposed BCC model, also known as VRS model, which further decomposed technical efficiency into pure technical efficiency and scale efficiency. However, both CCR model and VRS model can only evaluate the cross-section of each decision-making unit in a single year or period, but can't analyze the vertical section of several consecutive years or periods. That is, the traditional standard DEA method has natural shortcomings, because only the current input-output data are used to construct the optimal production frontier, and the results may appear the phenomenon of technological regression in dynamic analysis. Therefore, this study uses Malmquist index and DEA model to measure the temporal and spatial changes of total factor productivity in China's provinces.

Malmquist index was proposed by Swedish statistician Sten Malmquist in 1953. Fare et al. used Malmquist index to study production efficiency [7], and defined Malmquist productivity index as:

$$M=M(x_t, y_t, x_{t+1}, y_{t+1})=[\frac{d^t(x_{t+1},y_{t+1})}{d^t(x_t,y_t)} \times \frac{d^{t+1}(x_{t+1},y_{t+1})}{d^{t+1}(x_t,y_t)}]^{\frac{1}{2}}$$

$d^t(x_{t+1}, y_{t+1})$ represents the efficiency level of phase t+1 expressed by the technology of phase t (i.e., the data of phase t+1 is the reference set); $d^t(x_t, y_t)$ represents the efficiency level of phase t expressed by the technology of phase t (i.e., the data of phase t is tHhe reference set); $d^{t+1}(x_{t+1}, y_{t+1})$ represents the efficiency level of phase t+1 expressed by the technology; $d^{t+1}(x_t, y_t)$ represents the efficiency level of phase t expressed by phase t technology. M＞1 indicates that productivity is on the rise, whereas on the contrary, it is on the decline.

According to the analysis of Fare et al., the change of productivity, M can be decomposed into the product of technological efficiency change (effch) and technological change (techch) [8]. Its definition is as follows:

$$M=[\frac{d^t(x_{t+1},y_{t+1})}{d^t(x_t,y_t)} \times \frac{d^{t+1}(x_{t+1},y_{t+1})}{d^{t+1}(x_t,y_t)}]^{\frac{1}{2}}=\frac{d^t(x_{t+1},y_{t+1})}{d^t(x_t,y_t)} \times [\frac{d^t(x_{t+1},y_{t+1})}{d^{t+1}(x_{t+1},y_{t+1})} \times \frac{d^t(x_t,y_t)}{d^{t+1}(x_t,y_t)}]^{\frac{1}{2}}$$

$$=effch \times techch$$

Effch is an index of technological efficiency change, which describes the "catch-up effect" of decision-making units on the best production frontier from t to t + 1. Techch is an index of technological progress, which describes the movement of technological frontier from t period to t + 1 period ("growth effect"). Fare et al. decomposed the technical efficiency change index (effch) into pure technical efficiency change index (pech) and scale efficiency change index (sech) by solving the VRS model under the condition of variable returns to scale [8].

2.2 Data

This paper collects the input and output data of 31 provinces in agriculture from 07 to 16 years. The data are collected from the provincial statistical yearbooks and the official website of the National Bureau of Statistics, as well as from the original data processed. When considering the input and output indicators, the output indicators are divided into expected output and non-expected output [9]. The unexpected output is applied to DEA model [10]. The land, labor force, agricultural machinery and agriculture are selected [11]. The six corresponding indicators of fertilizer and livestock are the most important agricultural input indicators. Specific indicators are as follows:

Agricultural output variables: This paper chooses the total output value of agriculture, forestry, animal husbandry and fishery (RMB 100 million) as agricultural output variables.

Agricultural input indicators: (1) Land input, expressed by the total sown area of crops (1000 hectares). (2) Labor input is expressed by the number of primary industry employees (10,000 people). (3) Agricultural machinery input, expressed by the total power of agricultural machinery (10,000 kW). (4) the input of agricultural chemical fertilizer is expressed by the actual amount of chemical fertilizer applied to agricultural production in this year (10,000 tons), that is, the amount of pure agricultural chemical fertilizer applied (10,000 tons). (5) Irrigation input is expressed in terms of effective irrigation area (1000 hectares). Livestock input was expressed by the number of large livestock (cattle, horses, donkeys, mules, camels) at the end of the year. (6) Unexpected output, agricultural COD emissions (10,000 tons) and agricultural nitrogen and ammonia emissions (10,000 tons). The missing data were processed by the average of the proportion of agricultural COD emissions to total COD emissions in existing provinces.

3. Model Estimation and Results

3.1 Results

Using input-oriented MALMQUIST-DEA model with variable returns on scale, taking the total output value of agriculture, forestry, animal husbandry and fishery as expected output, agricultural COD emissions and agricultural nitrogen and ammonia emissions as unexpected output, DEAP2.1 was used to calculate the changes of total factor productivity of agriculture in the provinces from 2007 to 2016. In order to make a comparative analysis among regions, according to the seventh five-year plan and the latest division criteria of the Development and Reform Commission for the Western Regions proposed by the Party Central Committee and the State Council, this paper divides China into three regions: the eastern, the central and the western regions. The eastern region includes 11 provinces and municipalities: Beijing, Tianjin, Hebei, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong, Hainan and Liaoning; the central region includes 8 provinces and municipalities: Shanxi, Henan, Anhui, Jiangxi, Hubei, Hunan, Heilongjiang and Jilin; the western region includes 12 provinces and municipalities: Inner Mongolia, Guangxi, and Jilin. Chongqing, Sichuan, Guizhou, Yunnan, Tibet, Shanxi, Gansu, Qinghai, Ningxia and Xinjiang.

3.2 Time Difference Characteristics of Agricultural Productivity Change

The total factor productivity change index of China's agriculture and its decomposition are shown in Table 1. It can be seen that the annual average growth rate of TFP in 2007-2016 in China is 6.98%, mainly due to the change of 6.9% in technological progress. From the time dimension, the changes and characteristics of TFP in China's agriculture can be summarized as follows:

Table 1 Total Factor Productivity Change Index of China's Agriculture and Its Decomposition

Year	effch	techch	pech	sech	tfpch
2007-2008	1.016	1.157	1.023	0.994	1.176
2008-2009	1.005	1.051	1.000	1.005	1.056
2009-2010	0.994	1.149	1.003	0.992	1.142
2010-2011	1.004	0.856	1.017	0.987	0.859
2011-2012	1.005	1.098	1.005	1.000	1.103
2012-2013	1.019	1.077	1.007	1.013	1.097
2013-2014	0.996	1.076	0.993	1.003	1.072
2014-2015	0.969	1.088	0.974	0.994	1.054
2015-2016	1.003	1.442	1.019	0.984	1.446
Mean	1.001	1.069	1.00275	0.9985	1.069875

From the growth of TFP, except for negative growth in 2010-2011, the remaining eight periods of TFP are positive growth, which is basically similar to Zhou et al. (2014) study, indicating the credibility and comparability of the results. According to the decomposition index of TFP index, the growth of agricultural TFP in China mainly comes from the innovation and progress of production technology (6.9%), not from the improvement of agricultural technology efficiency (1%).

In terms of the trend of TFP growth over time, 2008, 2012 and 2015 are the three low periods of total factor productivity of agriculture in China. The troughs in 2008 and 2012 may be related to the outbreak of economic crises worldwide. China's agriculture has been affected by the depression of the world economic environment, and TFP has declined.

In the decomposition index of technological efficiency growth, pure technological efficiency and scale efficiency alternate in positive growth and negative growth, which can be clearly seen from the fluctuation of pure technological efficiency and scale efficiency around 1 in Fig. 1. It is precisely because of the continuous improvement of pure technical efficiency and scale efficiency that the agricultural technical efficiency of each region can be improved.

From the time-varying trajectory of agricultural TFP growth in the three regions, the central region increased from 23.3% in 2007 to 64.6% in 2016, while the eastern and western regions increased from 12.5% and 19.1% in 2007 to 36.3% and 48% in 2012 respectively. The three regions have a convergence trend in TFP growth.

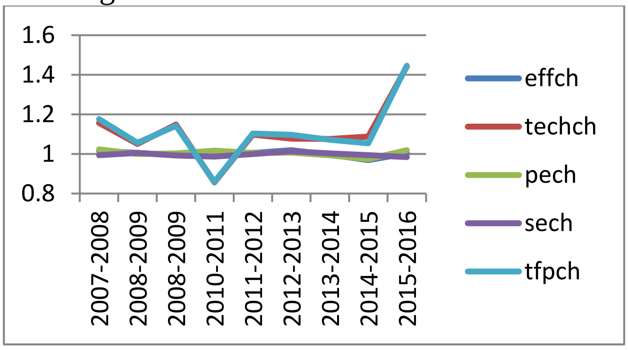

Figure 1 Decomposition of Total Factor Productivity Change of Agriculture in China from 2007 to 2016

3.3 Spatial Difference Characteristics of Agricultural Productivity

The change and decomposition of the total factor productivity index of agriculture in China's provinces are shown in Table 2. Meanwhile, the geometric average growth rates of the eastern, central and western regions are calculated. From the spatial perspective of provinces, the characteristics of agricultural TFP and its decomposition in China are as follows table 2.

According to the inter-provincial difference of TFP growth, the total factor productivity index of agriculture in all provinces increased positively, and the highest growth rate was Shaanxi (22%). From the average growth of TFP in the three regions, the agricultural TFP in the east, middle and west regions has achieved positive growth, with the fastest growth in the central region (11.6%), the second in the western region (11%) and the slowest growth in the eastern region (8.6%). Between the sea and 14.1% (Guangxi), the central region is between 6.9% (Jiangxi) and 16.8% (Shanxi), and the western region is between 5% (Tibet) and 18.6% (Shaanxi). It can be seen that the growth of agricultural TFP in China is not only quite different among the three regions, but also obvious among provinces within the region.

According to the decomposition index of TFP growth in each province, the growth of technological progress in eastern, central and western regions is much higher than that of technological efficiency. In terms of the growth of technological progress, the average growth rate in the central region is the highest (11.3%), followed by the western region (10.7%) and the eastern region (8.8%). In terms of provincial differences within the region, the eastern region is between 4% (Shanghai) and 11.8% (Liaoning), the central region is between 8.6% (Jiangxi) and 12.7% (Shanxi), and the western region is between 7.5% (Tibet) and 14.7% (Guangxi). In terms of technological efficiency, the eastern region has the slowest deterioration (-0.2%) and the central region has the lowest deterioration (-0.2%). It is almost the same as that in the West (0.3%). From the provincial differences within the region, the eastern region is between -2.3% (Guangdong) and 2.9% (Tianjin), the central region is between - 2.5% (Anhui) - 3.7% (Shanxi), and the western region is between -4.5% (Yunnan) - 5.3% (Shaanxi).

Table 2 Total Factor Productivity Index of Agriculture in China's Provinces and Its Decomposition

	effch	techch	pech	sech	tfpch
Beijin	1.000	1.076	1.000	1.000	1.076
Tianjin	1.029	1.060	1.020	1.009	1.091
Hebei	0.993	1.113	0.994	0.999	1.105
Shanxi	1.037	1.127	1.044	0.993	1.168
Neimenggu	1.005	1.119	1.000	1.004	1.124
Liaoning	1.000	1.118	1.000	1.000	1.118
Jilin	1.002	1.117	0.999	1.004	1.120
Heilongjiang	1.021	1.117	1.011	1.010	1.140
Shanghai	0.991	1.040	1.000	0.991	1.030
Jiangsu	1.000	1.106	1.000	1.000	1.106
Zhejiang	1.000	1.099	1.000	1.000	1.099
Anhui	0.975	1.116	0.977	0.998	1.088
Fujian	1.000	1.086	1.000	1.000	1.086
Jiangxi	0.984	1.086	0.984	1.000	1.069
Shandong	0.992	1.110	1.000	0.992	1.101
Henan	1.001	1.112	1.010	0.991	1.112
Hubei	1.001	1.117	1.019	0.982	1.117
Hunan	1.000	1.111	1.006	0.995	1.111
Guangdong	0.977	1.070	1.000	0.977	1.046
Guangxi	0.994	1.147	1.032	0.964	1.141
Hainan	1.000	1.085	1.000	1.000	1.085
Chongqing	1.006	1.100	1.003	1.004	1.107
Sichuan	0.983	1.094	1.000	0.983	1.075
Guizhou	1.048	1.103	1.047	1.001	1.156
Yunnan	0.955	1.128	0.968	0.987	1.078
Tibet	0.978	1.075	1.000	0.978	1.050
Shanxi	1.053	1.126	1.058	0.995	1.186
Gansu	0.990	1.109	0.990	1.000	1.098
Qinghai	1.022	1.079	1.001	1.020	1.102
Ningxia	1.011	1.086	0.992	1.020	1.098
Xinjiang	0.994	1.115	0.988	1.006	1.108
Eastern region	0.998	1.088	1.001	0.997	1.086
Central region	1.003	1.113	1.006	0.997	1.116
western region	1.003	1.107	1.007	0.997	1.110
China	1.001	1.102	1.005	0.997	1.104

According to the decomposition index of technological efficiency growth, the slowest growth rate of pure technological efficiency is in the eastern region (0.1%), followed by the central region (0.6%) and the fastest growth rate in the western region (0.7%). The scale efficiency deceleration rate is basically the same in the three regions (-0.3%).

4. Conclusion

Based on agricultural input-output data of 31 provinces and municipalities in China from 2007 to 2016, this paper uses MALMQUIST-DEA model to analyze the temporal and spatial characteristics of total factor productivity change and its decomposition in China's agriculture. The main conclusions are as follows:

From 2007 to 2016, China's agriculture has basically maintained a healthy and rapid development trend. During the sample period, the average annual growth rate of total factor productivity in China's agriculture was 6.98%, which played an important role in the growth of agricultural production in the same period. It showed that Chinese agriculture relied on various factors input, but also benefited from the continuous improvement of total factor productivity. From the composition of Malmquist productivity index, the dominant factor of agricultural TFP growth in China is the improvement of technological progress, not the improvement of agricultural technological efficiency.

After the environmental revision, the growth of agricultural TFP in the eastern, central and western regions of China was 8.6%, 11.6% and 11% respectively. This is different from the change of agricultural TFP growth measured by neglecting environmental factors in traditional research in China. The reason is that the good endowment conditions of agricultural resources in the eastern region of China, agricultural development has moved towards green and environmental protection earlier, and the growth of TFP value is relatively slow; while the natural and resource endowment conditions in the central and western regions of China are worse than those in the eastern region, but in recent years, along with a series of national policies to support the development of the central and Western regions. As well as the attention and attention to environmental protection issues, the central and western regions are transforming towards green and environment-friendly agriculture, and the TFP value is growing relatively fast.

According to the decomposition index of TFP growth, the growth of technological progress in eastern, central and western regions is much higher than that of technological efficiency. It can be seen that the growth of TFP in each province mainly comes from the innovation and progress of production technology, not from the improvement of agricultural technological efficiency, which is the same as the growth of agricultural TFP in the whole country. In addition, there is a certain degree of convergence in TFP, technological progress and technological efficiency growth in the three regions.

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