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Comparison of Total Factor Productivity of Rice in China and Japan

Liting Gao [1], Qianhui Gao [1,*] and Marcin Lorenc [2]

1 School of Economics and Management, China University of Mining and Technology, Xuzhou 221116, China; ts20070022a31@cumt.edu.cn
2 Department of Management and Production Engineering, Opole University of Technology, 45-758 Opole, Poland; m.lorenc@po.edu.pl
* Correspondence: qianhuigaocumt@126.com

Abstract: Because rice is one of China's staple foods, studying the total factor productivity (TFP) of rice is of great importance for China's food security. There are many similarities between rice production in China and Japan. Japan has achieved an effective supply of high-quality rice under the constraints of insufficient production resources and limited environmental capacity. In this paper, we use the DEA Malmquist index method to comparatively analyze the production efficiency of the rice industry in China and Japan, as well as its trends and changes. The contribution of each decomposition index is analyzed by using grey correlation, and kernel density estimation is used to analyze the dynamic evolution of rice productivity in both countries. The empirical results show that rice TFP in Japan is higher than that in China. Technological progress is an important driver of TFP and is the main reason for the difference in rice TFP between the two countries. The concentration of rice TFP distribution in China is decreasing, and regional differences are increasing, whereas in Japan, the opposite trend is observed, with the proportion of areas of high TFP increasing in both countries.

Keywords: total factor productivity; rice; DEA Malmquist

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1. Introduction

China is the largest rice producer in the world, with a total rice production of 149 million tons in 2021, accounting for about 30% of the world's total production [1]. China is also the largest rice consumer, with a demand of 155 million tons, representing about 30% of the world's total demand in 2021, and imports of 4.6 million tons [1]. In China, 60% of the population depends on rice as a staple food, representing one of the main food crops [2]. As shown in Figure 1, the supply and demand for rice in China have been stable over the years, but the requirement for rice has increased in recent years, with the demand exceeding the supply. Thus, improving total factor productivity of rice will become more important to ensure food security in China [3]. Rice production in China is also facing increasing resource constraints [4]. The massive use of pesticides and fertilizers has also brought a lot of negative impacts on the ecological environment, which is contrary to the concept of sustainable development. The efficiency of rice production can be improved by fully utilizing all factors and avoiding low output due to redundant or insufficient inputs, which is important for the sustainable development of the rice industry.

Japan is also one of the world's leading rice producers, achieving an effective supply of high-quality rice with only 0.03 hm^2 of paddy land per capita, with production and commercialization of high-quality rice above the global average. Japan is a typical country with a large population and scarce land, and its agricultural sector faces problems [5] such as scarce arable land, an aging rural labor force, and smallholder production, which are highly similar to China's agricultural development. Both countries have scarce arable land per capita [6,7] and are limited by resources and scale. Unlike the extensive agricultural economy in China, Japan has paid more attention to resources and environment, mainly relying on technology to improve unit yields. Given the similarity of agricultural endowments between the two countries, they can learn from one another in terms of agricultural policies and technologies. The analysis of rice productivity presented in this study can provide a positive implication for improving rice production, as well as promoting the sustainable development of the rice industry in China.

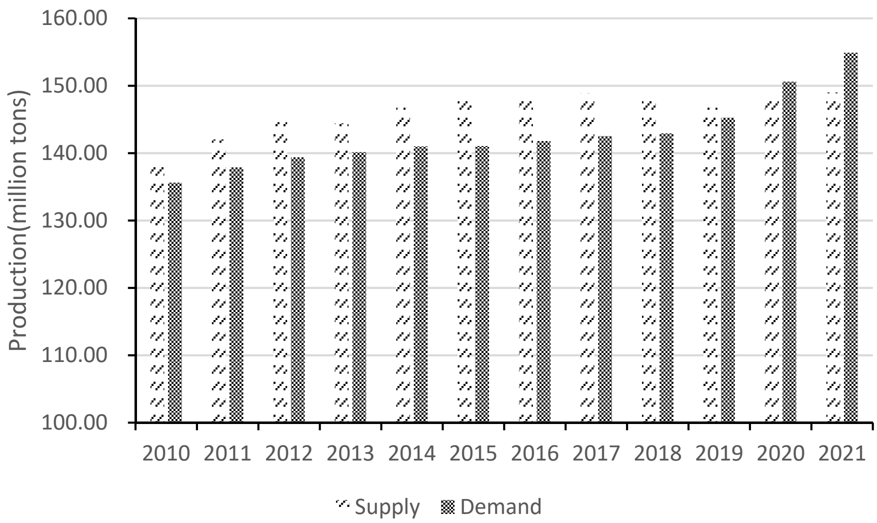

Figure 1. The supply and demand of rice in China's from 2010 to 2021. Source: http://worldfood.apionet.or.jp/graph/num.cgi, 3 January 2022.

Total factor productivity (TFP) is the counterpart to single-factor productivity, reflecting the weighted combined factor productivity of various factors, which is more comprehensive than the general concept of single-factor productivity [8]. Total factor productivity (TFP) growth involves both technological progress and improvements in technical efficiency [9]. The production frontier approach, which distinguishes between frontier technological progress and changes in technical efficiency by constructing optimal frontiers for production units, is the current mainstream approach to TFP accounting.

Previous studies have measured rice productivity in different countries using different methods. Umetsu et al. [10] used Malmquist productivity indices to examine regional differences in TFP, efficiency, and technological change in the Philippine rice sector of the post-Green Revolution era. Hossain et al. [11] applied the translog stochastic frontier production model (SFA) and data envelopment analysis (DEA) to estimate efficiencies over time, as well as the TFP growth rate for Bangladeshi rice crops. Donkor et al. [12] selected 470 smallholder rice producers from two districts in the Upper East region to analyze the factors influencing the efficiency of Ghana's rice industry using a stochastic meta-frontier model. Véronique Houngue et al. [13] estimated the technical and allocative efficiencies in Benin by using a stochastic frontier approach and the marginal value product approach. Krishna Prasad Devkota et al. [14] employed machine learning diagnostics, key performance indicator calculation, and dynamic simulation to characterize and decompose yield gaps for rice production in Nepal.

Earlier studies on the TFP of rice in China employed different perspectives. Hu Wen et al. [15] measured and decomposed TFP and its decomposition terms for 12 main Japonica-producing regions in China based on the factor endowments perspective using the DEA Malmquist index method and performed convergence tests between provinces. Xue Simeng et al. [16] conducted a comparative analysis of the production efficiency of the rice industry in China and Japan from 2004 to 2014 using the DEA Malmquist index method, with the yield per hectare of the main product as the output variable, on the basis of which astringency was tested. From the perspective of carbon emissions, Chen Zhukang et al. [17] analyzed the growth of the TFP of rice considering carbon emissions and provincial differences in China using the Malmquist–Luenberger productivity index based on directional distance function and a panel Tobit model. Dehua Zhang et al. [18] measured the production efficiency of China's main grain-producing regions from the perspective of grain subsidies, employing the DEA Malmquist index model, and analyzed the influencing factors in terms of spatial dimensions and index decomposition.

Previous research shows that there are well-established studies on TFP of rice and abundant discussion on the TFP of rice in China, whereas there is less literature on the measurement and analysis of rice production efficiency in Japan and even less literature on the comparative analysis of rice production between China and Japan. The main objective of this paper is to examine the driving forces of rice production in China and Japan and conduct a comparative analysis of the two countries across different regions and over time using the DEA Malmquist approach and kernel density estimation. Based on this empirical analysis, policy recommendations for the improvement of rice productivity and the sustainable development of the rice industry in China will be presented.

The main contribution of this paper is threefold. First, this study extends the literature on the comparative analysis of rice productivity between countries, whereas past studies have mainly focused on one country. Second, the impacts of technological progress and its three components on rice production in both China and Japan are quantitatively evaluated by employing the DEA Malmquist method. Third, in this study, we not only perform static time-series analysis but also further estimate the dynamic evolution of rice productivity in both countries by using kernel density estimation.

In this paper, the TFP of rice is measured and compared between China and Japan using one of the most popular methods of measuring TFP, the non-parametric DEA Malmquist index method, with the output value of the main product as the input variable. The correlation coefficients of each decomposition of TFP were measured by grey correlation analysis to assess the degree of influence of each factor. Furthermore, kernel density analysis was used to analyze the dynamic evolution of TFP in the rice industry in China and Japan.

2. Materials and Methods

2.1. Data Description

Considering the integrity and availability of data sets, the analysis in this study was based on rice yield and input in China and Japan from 2004 to 2018, including 18 provinces in China and 9 rural areas in Japan. The areas we chose cover the most rice-producing regions in the two countries. For measurement of efficiency, the following inputs were used: (I) biochemical inputs, which include the cost of seeds, fertilizers, farmyard manure, and pesticides; (II) mechanical inputs, which include the expenditures of machinery, energy, irrigation, and other mechanical materials; (III) labor inputs, including the cost of both families and hired labor for rice production. Owing to varying statistical standards, in the analysis, we used only direct labor to measure the labor inputs in Japan.

The study was carried out through a unified conversion of the data by multiplying the production costs per mu in China by 15 and per 10a in Japan by 10. The four variables involved in the study were treated in the same way. To eliminate the influence of price movements, the input and output variables were calculated by deflating the nominal values of the corresponding price indices. We used deflators in the agricultural price index from the two countries' statistical yearbooks.

2.2. Methodology

2.2.1. DEA Malmquist Index

The production frontier approach is the dominant method for TFP measurement specifically including both parametric and non-parametric methods. Numerous studies [19–24] have employed a non-parametric approach represented by the data envelopment approach (DEA), which uses linear programming and pairwise solutions without pre-determined functional forms. Several studies [25–28] have adopted parametric methods represented by the stochastic frontier production function, which uses econometric methods to estimate the unknown parameters in the frontier production function to determine the ratio of actual output to potential output. Compared with stochastic frontier analysis, the data envelopment approach (DEA) is more widely used because it can handle decision units with multiple input and output indicators at the same time and does not require a specific function.

In the present study, we applied the DEA Malmquist method to measure TFP in the rice industries of China and Japan, further decomposed into technical change, pure technical efficiency change, and scale efficiency change. The theoretical basis [29,30] of the DEA Malmquist index is as follows. Assume that the input vector and output vector for t (the base period) are x^t and y^t, respectively; and D^t. (x^t, y^t) represents the distance function in period t. To avoid possible differences due to arbitrary period selection, the geometric mean is used as the Malmquist index to measure productivity change from period t to period t + 1. The equation can be expressed as follows:

$$\begin{aligned} tfpch = M\left(x^{t+1}, y^{t+1}; x^t, y^t\right) &= \left\{\left[\frac{D^{t+1}\left(x^{t+1}, y^{t+1}\right)}{D^{t+1}\left(x^t, y^t\right)}\right]\left[\frac{D^t\left(x^{t+1}, y^{t+1}\right)}{D^t\left(x^t, y^t\right)}\right]\right\}^{1/2} \\ &= \frac{D^{t+1}\left(x^{t+1}, y^{t+1}\right)}{D^t\left(x^t, y^t\right)}\left\{\left[\frac{D^t\left(x^t, y^t\right)}{D^{t+1}\left(x^t, y^t\right)}\right]\left[\frac{D^t\left(x^{t+1}, y^{t+1}\right)}{D^{t+1}\left(x^{t+1}, y^{t+1}\right)}\right]\right\}^{1/2} \end{aligned} \tag{1}$$

If $tfpch > 1$, TFP increases over the period from t to t + 1; $tfpch < 1$ indicates that TFP decreases between t and t + 1; and $tfpch = 1$ suggests no change in TFP from t to t + 1.

The DEA Malmquist index can decompose the change in total factor productivity (tfpch) into two components: technical efficiency (effch) and technical progress (techch). Technical efficiency scores of the input-minimizing cases with constant returns to scale and represents the degree of efficiency in the allocation and use of resources. Technological progress means frontier shift during the period from moment t to moment t + 1, revealing the degree of change in production technology.

The change in technical efficiency can be expressed by the first term in Equation (1):

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

Furthermore, under the condition of variable returns to scale, technical efficiency change can be decomposed into pure technical efficiency change (pech) and scale efficiency change (sech), as shown as Equation (3), with the subscripts V and C denoting variable returns to scale and constant returns to scale, respectively.

$$effch = \frac{D^{t+1}\left(x^{t+1}, y^{t+1}\right)}{D^t\left(x^t, y^t\right)} = \frac{D_V^{t+1}\left(x^{t+1}, y^{t+1}\right)}{D_V^t\left(x^t, y^t\right)} \frac{D_C^{t+1}\left(x^{t+1}, y^{t+1}\right)/D_V^{t+1}\left(x^{t+1}, y^{t+1}\right)}{D_C^t\left(x^t, y^t\right)/D_V^t\left(x^t, y^t\right)} \tag{3}$$

The pure technical efficiency change can be expressed as:

$$pech = \frac{D_V^{t+1}\left(x^{t+1}, y^{t+1}\right)}{D_V^t\left(x^t, y^t\right)} \tag{4}$$

The scale efficiency change can be expressed as:

$$sech = \frac{D_C^{t+1}\left(x^{t+1}, y^{t+1}\right)/D_V^{t+1}\left(x^{t+1}, y^{t+1}\right)}{D_C^t\left(x^t, y^t\right)/D_V^t\left(x^t, y^t\right)} \tag{5}$$

The second term of Equation (1) can be arranged to denote the technical progress (techch) as follows:

$$techch = \left\{\left[\frac{D^t\left(x^t, y^t\right)}{D^{t+1}\left(x^t, y^t\right)}\right]\left[\frac{D^t\left(x^{t+1}, y^{t+1}\right)}{D^{t+1}\left(x^{t+1}, y^{t+1}\right)}\right]\right\}^{1/2} \tag{6}$$

Hence, the formulation of decomposition can be expressed as:

$$tfpch = effch \times techch = pech \times sech \times techch \quad (7)$$

2.2.2. Grey Relational Analysis

Grey relational analysis is a method to measure the degree of association between factors in a system [31]. By comparing the development and change trend of each factor in the system, the strength of the relationship between the factors is described quantitatively by the grey correlation degree. This method is based on the similarity of the geometry of the series curves to determine whether they are closely related or not; the closer the curves are, the greater the correlation between the corresponding series and vice-versa [32]. Compared with the traditional multifactor analysis method, grey correlation analysis requires fewer data points and is less computationally intensive, which makes it easy to be widely used. In the present study, we used this method to measure the degree of association between each of the decomposition indices.

2.2.3. Kernel Density Estimation

Kernel density estimation is a popular non-parametric method used to estimate the probability density function of a random variable, which essentially simulates the true probability distribution curve by fitting the data points of the sample with a kernel function. Kernel density estimation is more robust and less model-dependent than parametric estimation [33]. In this paper, we used kernel density estimation to analyze the dynamic evolution of TFP trends in the rice industry in both China and Japan. Epanechnikov kernel functions and an adaptive bandwidth estimator were employed.

3. Results and Discussion

Table 1 shows the descriptive statistics of the yield and three production factor inputs of rice. Except for the biochemical inputs in China, the means of other variables were higher than the medians, with a right-skewed distribution. The mean of labor input of China was higher than the sum of means of biochemical and mechanical inputs, which illustrates that the costs of labor were much higher than the expenditure of biochemical and mechanical inputs. In the case of Japan, the situation was different. The mean of mechanical inputs in Japan were higher than the other two inputs.

Table 1. Descriptive statistics of major variables.

China	Obs	Mean	Median	Std. Dev.	Min	Max
Labor	285	815.3447	717.070	558.4033	189.2471	2888.727
Biochemical	285	422.6361	425.445	150.4349	153.302	830.1892
Mechanical	285	375.3693	341.904	206.2095	94.33266	1231.229
Yield	285	2363.161	2342.531	867.0626	841.0551	4526.169
Japan	**Obs**	**Mean**	**Median**	**Std. Dev.**	**Min**	**Max**
Labor	165	3411.307	3286.93	917.8172	1792.44	5866.58
Biochemical	165	1778.576	1741.15	347.6223	1137.98	2618.56
Mechanical	165	4239.06	4038.05	1105.849	2272.38	7570.23
Yield	165	12,522.66	12,068.7	2991.869	7522.49	21,751.38

Source: (1) National Farm Product Cost-benefit Survey. (2) Ministry of Agriculture, Forestry and Fisheries, Situations about Rice.

As shown in Figure 2, per hectare costs of rice in China exhibited an increasing tendency. In particular, the growth rate of the labor expenditure was much larger than the biochemical and mechanical growth rates, and exceeded that of material capital (including the biochemical, mechanical, and other material inputs) in 2013. Biochemical costs were higher than mechanical costs, but the gap between them has narrowed over time.

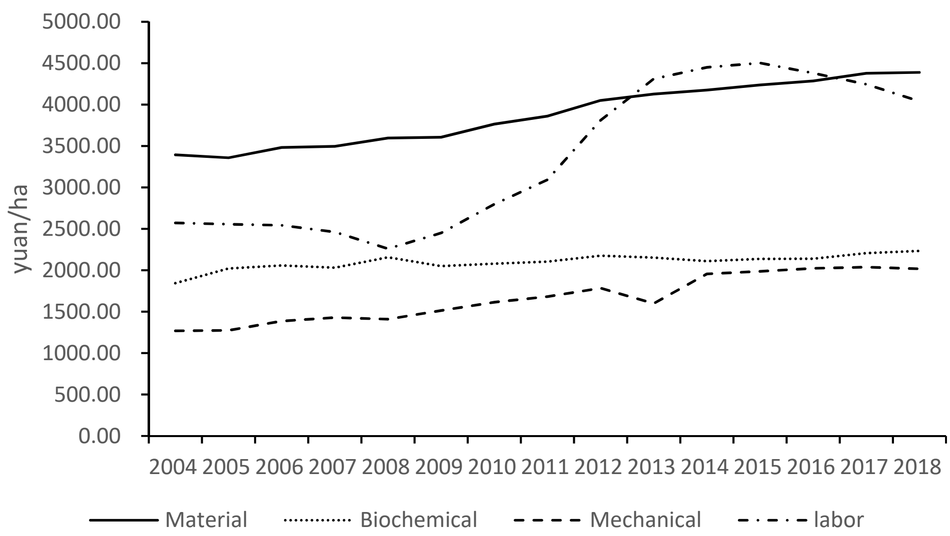

Figure 2. Per hectare cost of China's rice production from 2004 to 2018. Source: National Farm Product Cost-benefit Survey.

In contrast to China, labor expenditure was not a major expense associated with rice production in Japan, but material inputs accounted for roughly 70% of the total inputs. Mechanical inputs accounted for a much higher proportion than biochemical inputs, which was in contrast to China's situation. All input variables in Japan showed a similar variation, with less fluctuation and a decreasing trend (Figure 3).

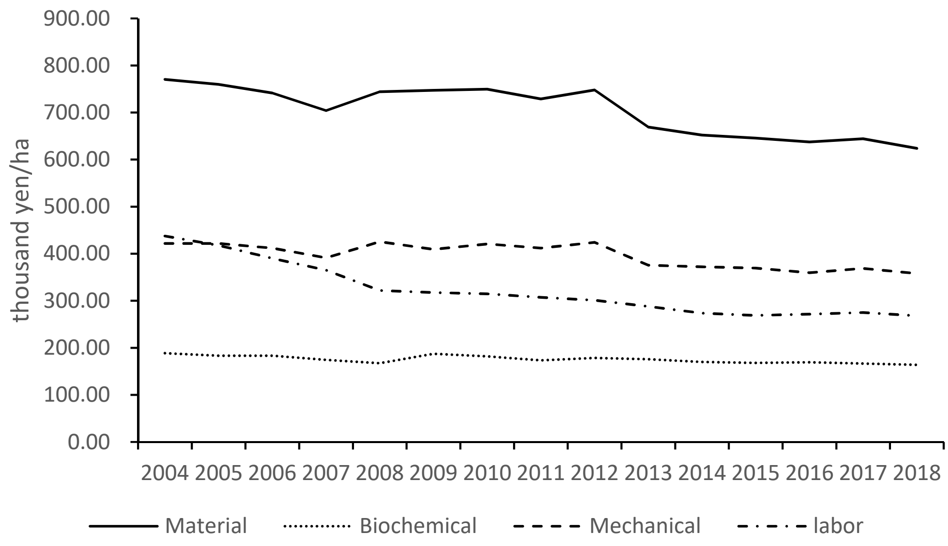

Figure 3. Per hectare cost of Japan's rice production from 2004 to 2018. Source: Ministry of Agriculture, Forestry and Fisheries, Situations about Rice.

3.1. Estimation of Rice Industrial Production Efficiency in China

3.1.1. Temporal Feature Analysis

The production efficiency index of the rice industry in China was calculated and decomposed based on the panel data of main product output value, labor input, mechanical input, and biochemical input per hectare in 18 provinces of China from 2004 to 2018.

As shown in Table 2, the TFP of rice in China regressed as a whole during the study period. Only half of the years showed progress in productivity. The average TFP change index was 0.978, with an average annual decline of 2.2%. According to the decomposition results of the Malmquist index, the average values of the technical efficiency and technical progress indices were 0.999 and 0.979, respectively, with a slight downward trend and an average annual decline of 0.1% and 2.1%, respectively.

Table 2. Malmquist index summary of annual means in China.

Year	Effch	Techch	Pech	Sech	Tfpch
2004–2005	1.051	0.850	0.996	1.055	0.893
2005–2006	0.911	1.028	1.003	0.908	0.937
2006–2007	1.082	0.958	1.006	1.075	1.036
2007–2008	0.942	0.905	0.934	1.008	0.852
2008–2009	1.026	1.238	1.081	0.949	1.270
2009–2010	0.987	0.895	0.977	1.009	0.883
2010–2011	1.015	0.855	0.988	1.027	0.867
2011–2012	1.001	1.139	0.993	1.008	1.139
2012–2013	0.954	1.142	0.959	0.994	1.089
2013–2014	0.909	0.795	0.916	0.992	0.723
2014–2015	1.212	0.943	1.181	1.027	1.143
2015–2016	0.901	0.997	0.912	0.988	0.898
2016–2017	0.973	1.081	0.990	0.983	1.052
2017–2018	1.067	0.980	1.056	1.011	1.046
mean	0.999	0.979	0.997	1.002	0.978

Technical efficiency is further decomposed in the condition of variable returns to scale and affected by the pure technical efficiency and the scale efficiency. The technical efficiency shows fluctuation basically consistent with the change in pure technical efficiency after 2007. The scale efficiency index has become less volatile since 2009, fluctuating within a range of only 3%. The pure technical efficiency index declined by 0.3%, and the scale efficiency increased by 0.2%. The improvement in scale efficiency illustrates that the policies of separating the three rights of land, encouraging rural land transfer, and promoting the large-scale operation of rice production have been successful.

Technological progress in rice production in China has declined by 2.1% annually, with only five years of technological progress. Possible reasons for the decline in technological progress include the following: (1) The escalating prices of production materials and labor force have increased the production cost of rice year by year, and cost margins have decreased significantly. According to the National Farm Product Cost-benefit Survey, the cost margins of rice production based on economic cost decreased from 62.71% to 5.38% in China from 2004 to 2018, and the cash cost-based cost margin decreased from 190.06% to 98.51%. As a result, producers are less motivated to adopt new planting techniques. (2) As improved methods such as hybrid rice and super rice have become widespread in China, the demand for these technologies by rice producers has reached saturation, and the impetus for an increasing rate of technological progress has waned.

From the perspective of the growth source of production efficiency, the TFP of rice production in China from 2004 to 2018 was jointly affected by technical efficiency and technological progress. After 2008, the trend of TFP tended to be consistent with technological progress, and the role of technological progress became more pronounced.

3.1.2. Temporal Feature Analysis

As shown in Table 3, among the 18 rice-producing provinces in China, only Guangdong, Guangxi, Fujian, and Anhui have made progress in terms of TFP. Among them, Anhui has exhibited largest increase, with an average annual growth rate of 3.2%. The TFP of the other 14 provinces has declined to varying degrees, with three provinces growing at a rate above the national average, seven provinces growing slightly below the average, and the remaining provinces declining more than the national average. Among them, Chongqing had the largest decline, with an average annual decline rate of 10.5%, which is 13.7% lower than that of Anhui. This indicates that there are large differences in the efficiency of rice production between regions in China. According to the data compiled from the China Statistical Yearbook, Chongqing's financial support ratio for agriculture was 8.67% from 2009 to 2018, which is lower than the national average of 9.4%, whereas the ratio in Anhui was 11.08%. The difference in the government's financial investment in agriculture one possible reason for the large difference in total factor productivity of rice between the two regions.

Table 3. Malmquist index summary of firm means in China.

Firm	Effch	Techch	Pech	Sech	Tfpch
Chongqing	0.961	0.931	0.965	0.997	0.893
Zhejiang	1.001	0.944	0.994	1.007	0.937
Yunnan	1.027	0.943	1.001	1.026	1.036
Sichuan	1.013	0.957	1.001	1.012	0.852
Liaoning	1.001	0.965	1.000	1.001	1.270
Jiangxi	1.010	0.967	1.005	1.005	0.883
Jiangsu	0.999	0.977	1.002	0.998	0.867
Jilin	0.997	0.978	1.000	0.997	1.139
Hunan	1.005	0.972	1.003	1.002	1.089
Hubei	1.013	0.973	1.012	1.002	0.723
Heilongjiang	1.011	0.966	1.008	1.003	1.143
Henan	0.996	0.960	1.000	0.996	0.898
Hainan	0.992	0.993	0.994	0.998	1.052
Guizhou	0.994	0.996	0.999	0.996	1.046
Guangxi	0.998	1.006	1.002	0.996	0.978
Guangdong	0.990	1.016	0.994	0.997	1.006
Fujian	0.987	1.034	0.989	0.999	1.021
Anhui	0.985	1.048	0.985	1.000	1.032
mean	0.999	0.979	0.997	1.002	0.978

The decomposition of the TFP index shows that technical efficiency improved in nearly half of the provinces, whereas only four provinces improved technologically, consistent with the four provinces with $tfpch$ greater than 1. The range of the technological progress index is 11.7%, indicating that there are considerable differences in technological progress with respect to rice planting. Under the condition of variable returns to scale, technical efficiency can be further decomposed into pure technical efficiency and scale efficiency. The pure technical efficiency of the eight provinces has increased, indicating that productivity has been improved by simply using the input factors of production. The pure technical efficiency of Liaoning and Hunan provinces has remained unchanged, whereas the pure technical efficiency of other provinces has declined slightly. Scale efficiency generally improved through changes in the scale of production factor inputs, but the improvements were small. Seven provinces achieved improvements in scale efficiency, whereas Anhui remained unchanged and the other provinces presented a scale efficiency index of less than 1. The overall performance of scale efficiency is optimistic.

Overall, the progress of TFP is mainly driven by technological progress. As shown in Table 2, provinces with technological progress above the national average also lead the level of progress. Technological progress lags behind the national level, whereas provinces that have improved their technical efficiency have not performed well in terms of TFP. This indicates that it is difficult to drive progress in the TFP of rice production in China by relying simply on improvements in technological efficiency.

3.2. Estimation of Rice Industrial Production Efficiency in Japan

The production efficiency index of the rice industry in Japan was calculated and decomposed based on the panel data of main product output value, labor input, mechanical input, and biochemical input in nine rural areas of Japan from 2004 to 2014. The results are shown in Table 4.

Table 4. Malmquist index summary of annual means in Japan.

Year	Effch	Techch	Pech	Sech	Tfpch
2004–2005	1.097	0.962	1.028	1.067	1.056
2005–2006	1.037	0.892	0.999	1.038	0.925
2006–2007	0.967	1.277	1.001	0.966	1.235
2007–2008	1.004	1.180	0.987	1.017	1.185
2008–2009	1.014	0.817	1.006	1.009	0.829
2009–2010	1.021	1.158	1.008	1.013	1.182
2010–2011	0.962	1.166	0.989	0.973	1.122
2011–2012	0.836	0.992	0.846	0.988	0.829
2012–2013	1.207	0.768	1.202	1.004	0.927
2013–2014	0.990	1.350	0.996	0.994	1.336
2014–2015	1.040	0.979	0.994	1.046	1.018
2015–2016	0.955	1.098	1.006	0.949	1.048
2016–2017	1.017	0.994	1.002	1.015	1.010
2017–2018	0.980	1.134	1.000	0.979	1.111
mean	1.006	1.042	1.002	1.004	1.048

Rice production in Japan was optimistic during the period from 2004 to 2018. The average TFP change index was 1.048, with an average annual growth of 4.8%. Four of the years showed a recession, whereas the other years showed productivity progress. The decomposition of TFP change shows that both technical efficiency and technical progress improved, with mean values of 1.006 and 1.042, respectively. The amplitude of technological progress is greater than that of technical efficiency, with an average annual growth of 4.2%.

Technical efficiency grew at an average annual rate of 0.6%, which was further decomposed to yield an average annual increase of 0.2% for pure technical efficiency and 0.4% for scale efficiency, with relatively small fluctuations overall. With the development of industrialization, a large number of labor transfers from agriculture to non-agricultural industries, as well as the mechanization of rice production in Japan, has contributed to the improvement in technical efficiency to some extent.

Technological progress in rice production in Japan has improved, with an average annual increase of 4.2% in the period from 2004 to 2018. Possible reasons are as follows: (1) Japanese farmers have a high level of literacy and are more receptive to new technologies. In addition, high land prices and high agricultural population density also drive farmers to actively learn and adopt new technologies. (2) With the development of smart agriculture in Japan, intelligent production management and agricultural information dissemination mechanisms, which use computer networks as an important path, are increasingly improved. Agricultural staff can analyze and judge accurate and timely data in real time. (3) With the development of environmentally friendly agriculture in Japan, the certification system and subsidy system of eco-agriculture and organic agriculture have stimulated the enthusiasm of rice producers to use modern biological varieties and innovative chemical fertilizer technology.

From the perspective of the growth source, the variation of production efficiency in the rice industry is caused by both technical efficiency and technological progress. However, the contribution of technical progress is greater than that of technical efficiency.

As shown in Table 5, the rice production efficiency of the nine rural areas in Japan improved during the period from 2004 to 2018, and the difference in growth across regions is small. The largest increase in productivity was observed in Tokai, with an average annual increase of 6.4%, differing by only 3.3% from the slowest growth rate in Hokkaido. According to the decomposition results of the Malmquist index, the change in technical efficiency is small. That is, the change in input–output efficiency achieved through the efficient use of input factors of production is small when production technology is assumed to be constant in these regions.

Table 5. Malmquist index summary of firm means in Japan.

Firm	Effch	Techch	Pech	Sech	Tfpch
Chugoku	1.006	1.033	1.002	1.003	0.893
Shikoku	1.019	1.035	1.009	1.010	0.937
Kyushu	1.012	1.041	1.001	1.011	1.036
Kinki	1.008	1.041	1.005	1.003	0.852
Kanto	0.992	1.040	0.999	0.993	1.270
Tokai	1.014	1.050	1.003	1.010	0.883
Tohoku	1.017	1.045	1.002	1.015	0.867
Hokuriku	0.999	1.048	1.000	0.999	1.139
Hokkaido	0.989	1.043	1.000	0.989	1.089
mean	1.006	1.042	1.002	1.004	0.723

The index of change in technical efficiency was slightly less than 1 in three provinces, and technical efficiency improved in the other regions. Under the condition of variable scale, the variation of pure technical efficiency and scale efficiency in each region is less than 1%. Technological progress is the main driver of TFP growth. The technological change index of nine rural areas in Japan was greater than 1, which means that all areas achieved technological progress. Tokai achieved the most significant technological progress, with an average annual growth rate of 5%, and its TFP growth was also greater than that of other areas. Technical efficiency factors also played an important role in the growth of TFP. The technical efficiency index of Hokkaido was the lowest, and its TFP also grew at the slowest rate compared with other areas affected by this factor.

3.3. Grey Relation Analysis of TFP Decomposition Index

According to the grey correlation analysis method, the correlation coefficients of TFP (Table 6) with technical efficiency and technical progress of rice in China are 0.656 and 0.767, respectively. This indicates that the TFP of rice in China is mainly affected by technological progress, which can compensate for the loss of efficiency. This demonstrates the role of mature technology efficiency but also reflects the limited promotion of new rice technology in recent years. The findings are consistent with those of the DEA Malmquist analysis. The correlation coefficients of comprehensive technical efficiency with pure technical efficiency and scale efficiency are 0.780 and 0.715, respectively. This indicates that pure technical efficiency and scale efficiency of rice in China jointly affect comprehensive technical efficiency.

Table 6. Correlation coefficients of TFP decomposition indices of rice in China and Japan.

Country	Correlation Coefficient of Tfpch with Effch and Techch		Correlation Coefficient of Effch with Pech and Sech	
	e1	e2	e1	e2
China	0.656	0.767	0.780	0.715
Japan	0.622	0.658	0.617	0.714

In Japan, the correlation coefficients of TFP with technical efficiency and technological progress in rice production are 0.622 and 0.658, respectively, indicating that technical efficiency and technological progress act together on TFP. The correlation coefficients of comprehensive technical efficiency with pure technical efficiency and scale efficiency are 0.617 and 0.714, respectively, indicating that the comprehensive technical efficiency of Japanese rice production is mainly influenced by scale efficiency.

In Japan, the correlation coefficients of TFP (Table 6) with technical efficiency and technological progress in rice production are 0.622 and 0.658, respectively, indicating that technical efficiency and technological progress act together on TFP. The correlation coefficients of comprehensive technical efficiency with pure technical efficiency and scale efficiency are 0.617 and 0.714, respectively, indicating that the comprehensive technical efficiency of Japanese rice production is mainly influenced by scale efficiency.

3.4. Comparison of Rice Production Efficiency between China and Japan

From the perspective of dynamic changes, TFP in the rice industry in Japan is higher than that in China. From 2004 to 2018, China's rice production efficiency declined by 2.2% annually, whereas that of Japan increased by 4.8% annually. Specifically, Japan's technical efficiency and technological progress indices are higher than those of China. A relatively large gap in technological progress between the two countries represents an important reason for the difference in productivity growth.

With respect to the growth source of production efficiency, the TFP of rice production in China is mainly driven by technological progress, whereas in Japan, it is caused by a combination of technological efficiency and technological progress. China's technical efficiency and technical change indices have declined, whereas those of Japan have increased, with a difference of 0.7% and 6.1%, respectively.

From the perspective of further decomposition of technical efficiency, the comprehensive technical efficiency of rice production in China is the result of the combined effect of pure technical efficiency and scale efficiency, whereas in Japan, it is mainly affected by scale efficiency. The scale efficiency of both countries has improved, but the magnitude is small; that is, the change in TFP is relatively insignificant after adjusting the scale of inputs. Pure technical efficiency improved in Japan and regressed in China, but the magnitude was within 0.5%; that is, the magnitude of TFP change achieved through efficient use of input factors was also small after removing changes in scale efficiency.

Technological progress is an important driving force of TFP progress for rice production in both China and Japan. As shown in Tables 7 and 8, the minimum value of Japan's technological progress index is greater than 1; that is, rice production in Japan's nine rural areas achieved technological progress during the period from 2004 to 2018, whereas only four provinces in China improved technological progress. The means and medians of the Malmquist index for all regions in China are smaller than those in Japan, and only the extreme values of individual indicators are larger than those for Japan, indicating that the progress of rice production efficiency in all regions of China lags behind that of Japan. Compared with Japan, rice production efficiency varies greatly in China. The regional differences in the technological progress and TFP indices in China are 11.7% and 13.7%, whereas in Japan, they are only 1.7% and 3.3%, respectively.

Table 7. Descriptive statistics of Malmquist index of China.

China	Obs	Mean	Median	Std. Dev.	Min	Max
effch	18	0.999	1.001	6.50%	0.958	1.023
techch	18	0.982	0.978	9.40%	0.943	1.037
pech	18	0.996	1.001	5.30%	0.958	1.011
sech	18	1.003	1.001	2.80%	0.995	1.023
tfpch	18	0.981	0.983	13.50%	0.903	1.038

Table 8. Descriptive statistics of Malmquist index of Japan.

Japan	Obs	Mean	Median	Std. Dev.	Min	Max
effch	9	1.006	1.008	3.00%	0.989	1.019
techch	9	1.042	1.041	1.70%	1.033	1.050
pech	9	1.002	1.002	1.00%	0.999	1.009
sech	9	1.004	1.003	2.60%	0.989	1.015
tfpch	9	1.048	1.050	3.30%	1.031	1.064

The gap in technological progress is the main factor contributing to the difference in rice productivity growth between the two countries. Possible reasons for the technology difference between these two countries are as follows: (1) The proportion of financial expenditures associated with agricultural research in China is lower than that in Japan. According to the FAO, a country's public investment in agricultural science and technology needs to be at least 2% so that its agricultural development can be adequately supported by science and technology [34]. Since 2007, this ratio has exceeded 4% in Japan, and in 2010 and 2011, it exceeded 5%, which is much higher than the current average of 2.37% in developed countries [34]. (2) Farmers in China are less educated than those in Japan, and their acceptance of new technologies is weaker [35]. By the end of 2017, more than 90% of China's agricultural workers were educated at a junior high school level or below [36]; in comparison, Japan's overall high school enrollment rate exceeded 90% in 1975 and has remained above 95% since 1992 [36,37]. (3) The conversion rate of agricultural science and technology in China is lower than that in Japan. Since China's 13th Five-Year Plan, the contribution rate of agricultural technology progress has exceeded 60% [38]. However, in Japan, the contribution rate reached 75% after the Second World War [39].

3.5. Kernel Density Estimation

The above analysis is based on the time-series changes of TFP in rice production in China and Japan, as well as the average development trend. We used kernel density estimation is used in order to depict the dynamic evolution of TFP, that is, the distribution pattern over time, in a more detailed and intuitive way.

Figure 4 shows the dynamic evolution of TFP in 18 rice-growing regions of China from 2004 to 2018. The TFP of rice in China showed a clear bimodal distribution in 2010. In other periods, the distribution of peaks was basically unimodal, with the right side of the curve bulging outward with a rising trend, indicating that with the passage of time, it is more likely to appear as double peaks. This shows that the TFP of rice production in China was polarized in 2010, and the polarization weakened afterwards, although the trend still exists. The center of the curve moved to the right, and the height of the wave decreased in 2010 and remained stable thereafter. The main peak kurtosis was weakened, and the wave peak was more subdued. This indicates that the TFP of rice increased in most provinces of China during the study period, although discretely. The interval of the kernel density curve did not change significantly during the period under examination, but the right-trailing tail gradually lengthened, indicating that regional differences in rice TFP in China were not effectively controlled, and the number of provinces with high levels of TFP increased.

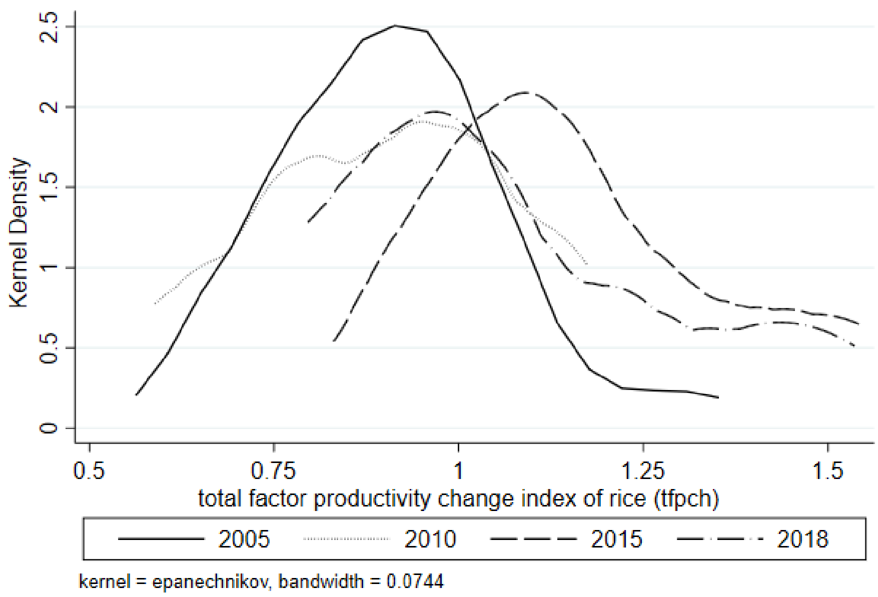

Figure 4. Kernel density estimation of TFP change index of rice in China.

Compared to 2005, the peak in 2010 was smaller, with a weaker peak, a bimodal distribution, and a narrower range of variation, indicating a more concentrated and polarized distribution of TFP during this period. The curve shifted significantly to the right in 2015, with the interval increasing and the curve changing from a 'double-peak' to a 'single-peak' distribution compared to 2010 and the peak leveling off after a steep decline. This indicates that TFP increased significantly in this period and that polarization was controlled, although regional differences remained large. By 2018, the kernel density curve flattened out more, with the right tail growing significantly. The center of the curve shifted leftward, and the concentration of the distribution decreased. This indicates a decline in TFP during the period, with regional differences remaining unabated, although the proportion of provinces with higher levels of TFP increased. The right-hand tail of the curve bulged significantly, showing a trend towards polarization.

Figure 5 depicts the dynamic evolution of TFP of rice in nine rural areas in Japan from 2004 to 2018. The kernel density curve basically shows a single-peak distribution with decreasing wave height and diminishing kurtosis during the examination period. Over time, the right tail became evident, with a skewed distribution. This suggests that there is a low convergence in TFP of rice in Japan, whereas the proportion of areas with higher TFP is increasing.

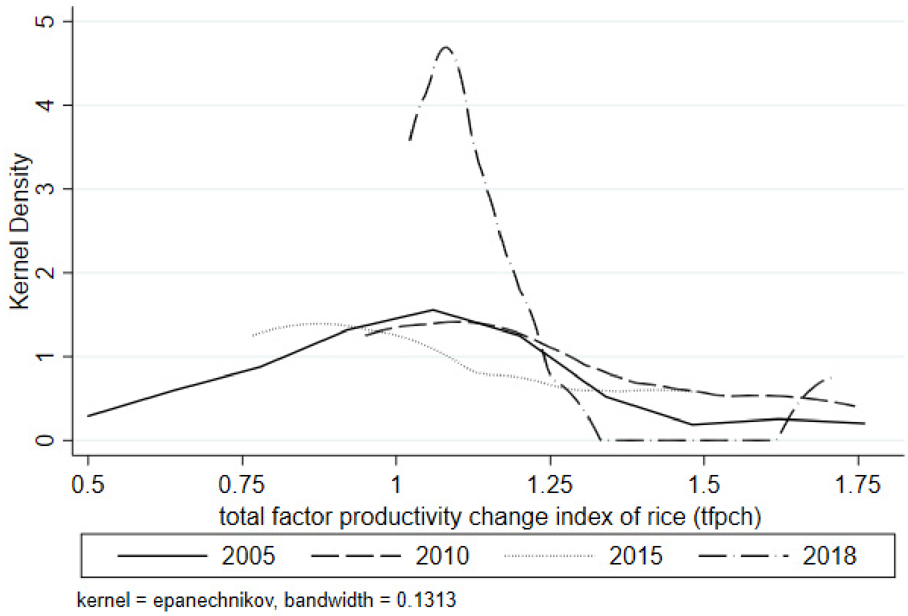

Figure 5. Kernel density estimation of TFP change index of rice in Japan.

Compared to 2005, the curve shifted slightly to the right in 2010, with a narrowing of the interval and a decline in the crest. The left tail of the curve shortened significantly, and the right tail elongated. This indicates that the proportion of regions with lower levels of TFP in rice in Japan decreased significantly during this period, and the proportion of regions with higher levels increased. TFP has increased in most regions, and the differences between regions have narrowed.

The center of the curve shifted to the left after 2010, indicating a regression in TFP in most regions after 2010. No significant change in the shape of the density function curve occurred in 2015 compared to 2010. In contrast, in 2018 compared to 2015, the center of the curve shifted to the right, the peak rose sharply, the interval narrowed, and the wave broke after a steep decline before forming a bimodal distribution. This indicates that the concentration of the distribution increased during this period, with most regions progressing in terms of TFP and a phenomenon of polarization.

In terms of the distribution of TFP, the concentration of the distribution in China has decreased, whereas in Japan, it first decreased and then increased. In terms of regional differences, the change in regional gaps in China is more stable, with a limited trend of expansion, whereas the regional variations in Japan continue to decrease. Both countries have a pronounced right tail in the kernel density graph, with a tendency to lengthen. This indicates that the proportion of regions with higher levels of TFP has increased in both countries, and the proportion of regions with lower levels of TFP is decreasing in Japan.

4. Conclusions and Policy Recommendations

4.1. Conclusions

1. The DEA Malmquist index shows that TFP in rice production was higher in Japan than in China during the period under study, especially with regard to technological progress. Both countries have achieved improvements in technical efficiency, but neither country has generated large fluctuations in TFP through the efficient use of input factors and adjustment of input scale.
2. Grey relational analysis reveals that for both China and Japan, technological progress is the main driver of TFP development in rice production, and technological progress can compensate for the loss of efficiency. Compared to Japan, China's TFP is more strongly correlated with technological progress. The gap in technological progress is the primary reason for the productivity gap between the two countries. The difference in technological progress between the two countries is related to the investment of financial expenditures for R&D and the conversion rate of agricultural science and technology achievements.
3. The regional disparities in TFP of rice production in China are more serious than those in Japan. Moreover, in terms of the dynamic evolution of TFP, the regional differences in the TFP of rice production in China also showed a tendency to widen, whereas the opposite trend was observed in Japan. The proportion of high-level areas of TFP of rice production in both countries also gradually increased, and that of low-level areas was decreased.

4.2. Policy Recommendations

Based on the above analysis, the policy implications are as follows:

1. For both China and Japan, it is recommended to rely on technology rather than a large number of factor inputs to improve the yield and productivity of rice. Extensive modes of agriculture development do not work well in terms of improving rice productivity. Based on the national situation of small farmers in a large country, China can reference some policies of Japanese agriculture, such as by promoting the development of smart agriculture and relying on machines and technology to improve labor productivity, using the progress of agricultural science and technology to facilitate the sustainability of the rice industry.
2. China should emphasize and invest more in agricultural science and technology. The innovation of agricultural science and technology is the main factor in sustainable agriculture development [40], and technological innovation in agriculture requires financial support. The intensity of China's investment in agricultural research is much lower than that of developed countries and some developing countries. It is necessary for government to increase expenditure with respect to agricultural technology research. On the other hand, China should improve the transformation rate of agricultural science and technology achievements by raising the awareness of rice producers of scientific farming and fully applying agricultural technology to rice production.
3. The regional differences in TFP of rice production in China are widening, which is detrimental to the improvement and sustainability of the rice industry in the long term. The central government should direct more financial support to provinces that are lagging behind in agricultural technology. On the other hand, the government can improve agricultural information dissemination mechanisms and promote technology diffusion from areas with high levels of agricultural technology to other areas. Japan's

intelligent agricultural information dissemination mechanism based on the path of computer networks has greatly improved the efficiency of information dissemination compared with China, where there is still much room for improvement.

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