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Analysis of Spatial Unbalance and Convergence of Agricultural Total Factor Productivity Growth in China—Based on Provincial Spatial Panel Data From 1978 to 2020

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Abstract: Using the provincial panel data from 1978 to 2020 as the research object, this study employs the fixed effect SFA-Malmquist model to measure the agricultural total factor productivity of each province and city, and the spatial correlation of China's agricultural total factor productivity is determined by Moran's I. On this basis, three weights (adjacency, economy, geography) are included as spatial factors in three spatial β-convergence models (SAR, SEM and SDM), and the spatial convergence characteristics of China's agricultural total factor productivity are analyzed in different time periods and different regions. The study found that: First, China's agricultural total factor productivity shows a growing trend, but as time goes on, its growth rate gradually slows down, and the growth rate in the eastern region is higher than that in the central and western regions. Second, China's agricultural total factor productivity has significant spatial correlation and spatial convergence characteristics. The differences in agricultural total factor productivity in various regions are shrinking over time, and the spatial spillover effect significantly shortens the convergence process. Due to spatial convergence, while carrying out agricultural production, all regions should thoroughly consider the advantages of agricultural resources in neighboring regions and strengthen cooperation and exchanges between regions.

Keywords: agriculture; total factor productivity; spatial convergence; unbalance

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1. Introduction

Agricultural production is an important foundation for national stability and security (Hou & Yao, 2018). Since 1978, relying on the increase of factor input and the improvement of total factor productivity, China's agriculture has made great achievements. The output and productivity of all major agricultural sectors have increased rapidly (Gong, 2018b; Lin, 1992). It has created a miracle that less than 10 % of the world's arable land has fed 20 % of its population (Li, 2014). The total agricultural output increased from 111.8 billion yuan in 1978 to 7174.8 billion yuan in 2020. However, with the increasing scarcity of land resources, the shortage of rural labor force caused by the acceleration of urbanization, and the diminishing marginal returns caused by the continuous improvement of fertilizer and machinery inputs, the contribution of the increase in agricultural factor inputs to agricultural growth is constantly decreasing. The way to promote agricultural development by relying on factor inputs is unsustainable. Continuously improving agricultural total factor productivity has almost become the only choice (Gao, 2015; Yang & Yang, 2013).

Due to the critical role of total factor productivity (TFP) in agricultural production, TFP has become an essential focus of scholars at home and abroad. Scholars use different methods (parametric methods and nonparametric methods), different data (macro statistical data, micro survey data), and different production function settings (Translog production function or C-D function) to measure China's agricultural TFP to make an accurate judgment on the trend of China's agricultural TFP and its key influencing factors (Pan & Ying, 2012). Still, the existing research has not reached a more consistent conclusion. This difference is not only reflected in the measurement value of China's agricultural TFP (Wu et al., 2001; Xu, 1999). More importantly, they have severe differences in China's agricultural TFP trend after the 1990s (Gong, 2018a). Some scholars believe that the growth rate of China's agricultural TFP continued to increase in the late 1990s and began to slow down until 2000 (Nin Pratt et al., 2008; Wang et al., 2013). Other scholars believe that the growth rate of China's agricultural TFP has slowed down since the 1990s (Chen et al., 2008; Zhou & Zhang, 2013).

In addition, since 1978, with the improvement of China's agricultural market and the continuous improvement of regional openness and exchange, the flow of agricultural production factors between regions has become increasingly frequent (Wu, 2010). Spatial factors have become a negligible factor affecting China's agricultural TFP, but few scholars have included spatial factors in the analysis of agricultural TFP (Wang et al., 2010). Productivity caused by differences in resource endowments and agricultural development levels in different regions spatially distributed? How will this spatial difference evolve? Does the difference in total factor productivity among regions show a convergence trend over time? If so, what form of convergence? What are the characteristics of convergence in different regions and stages of development? Therefore, the scientific measurement of China's agricultural TFP since 1978 and the analysis of its differences in spatial distribution and the convergence law over time will help to understand the growing trend of China's agricultural TFP since the reform and opening up. An objective understanding of the spatial differences and temporal evolution of agricultural TFP is of great significance for strengthening the scientific flow of agricultural production factors between regions, the sustainable development of China's agriculture, and the realization of modern agriculture.

2. Literature Review

Based on the critical role of TFP in China's agricultural development, scholars have conducted detailed and in-depth research on it, which has laid a good foundation for the writing of this paper. Throughout the existing literature, the research on China's agricultural TFP can be elaborated from three aspects: research methods, research contents, and research conclusions.

Research methods. Currently, the mainstream methods for measuring the TFP of China's agriculture are Data Envelopment Analysis (DEA) and Stochastic Frontier Analysis (SFA). Huo et al. (2011), Yang and Yang (2013), Wang and Zhang (2018) all used the DEA method to measure the TFP of Chinese agriculture. Considering that agricultural production is a complex process and will be affected by many factors in the production process, DEA can only consider the primary input and cannot attribute other factors to the residual term, which may affect measurement accuracy to a certain extent (Shi et al., 2016). For this reason, some scholars suggest using the SFA method to measure the TFP of China's agriculture. Quan (2009), Kuang (2012), Zhang and Cao (2013) began to use the SFA method to measure China's agricultural TFP. Although the total factor productivity measured by the SFA method is more in line with the characteristics of agricultural production, and the measurement results are better than DEA to a certain extent (Fan & Li, 2012), the existing literature on the measurement of agricultural TFP by SFA ignores the personal effect in the non-efficiency term, which may overestimate the technical efficiency, thus affecting the measurement results of TFP (Kumbhakar, 1990).

In the research content aspect, the scholars' research on agricultural TFP has been measured in detail from different levels, such as micro (Gao et al., 2016; Jia & Xia, 2017) and macro (Wang & Zhang, 2018), and the critical factors affecting TFP have been studied (Li & Yin, 2017; Zeng et al., 2018). However, the above studies regard different regions as independent individuals and do not include the inter-regional flow of production factors and the resulting spatial relationship. With the development of spatial econometrics and economic geography, some scholars began to consider the role of spatial factors in agricultural production. For example, Wang et al. (2010) used the spatial econometric model to study the growth of China's agricultural TFP and its influencing factors from 1992 to 2017. Yang and Yang (2013) studied the spatial correlation of China's agricultural TFP and concluded that the agricultural TFP in the adjacent areas has obvious spatial effects.

In terms of research conclusions, there are some differences in the existing research on the measurement value of China's agricultural TFP. For example, for the study of the average annual growth rate of China's agricultural TFP from 1981 to 1995, Xu (1999) showed that the average annual growth rate of the above interval was −1.48 %, while Wu et al. (2001) obtained an average annual growth rate of 2.41 %. In addition, scholars have significant differences in the trend of China's agricultural TFP after the 1990s (Gong, 2018a). Nin et al. (2008), Wang et al. (2013) believe that the growth rate of China's agricultural TFP continued to increase in the late 1990s, while Chen et al. (2008), Zhou and Zhang (2013) believe that the growth rate of China's agricultural TFP has slowed since the 1990s.

In summary, the existing literature can still be expanded from the following aspects. Considering that the SFA method has more advantages than DEA in the measurement of agricultural TFP, the existing research on the measurement of agricultural TFP using SFA ignores the individual effects in the non-efficiency term, so the SFA-Malmquist method with fixed effects can be used to solve this problem. In addition, with the strengthening of inter-regional exchanges, spatial factors play an increasingly important role in agricultural production. The convergence model considering spatial effects can deeply analyze the evolution of agricultural TFP in time and space. Based on this, this paper will take China's provincial agricultural production data from 1978 to 2020 as the research unit and use the fixed effect SFA-Malmquist model, which can separate the individual effect and the non-efficiency term to re-measure China's agricultural TFP. On this basis, Moran's I and spatial convergence model are used to study the evolution of agricultural TFP in time and space and the influence of spatial factors on agricultural TFP.

3. Research Methods

3.1. Fixed Effect SFA-Malmquist Model

DEA and SFA are the mainstream methods to measure Total factor productivity (TFP), the Malmquist index is a specific index established by Caves et al. (1982) to measure the change in total factor productivity based on the Malmquist consumption index and Shepherd distance function. In practical research, the distance function in the Malmquist index is generally calculated by parametric methods (such as SFA) or non-parametric methods (such as DEA) and then decomposed (Shi et al., 2016). As mentioned before, the agricultural production process is affected by many factors. SFA can incorporate these random factors into the classical white noise term and has more advantages than the DEA method in measuring agricultural production efficiency. Considering that previous studies ignore the individual effects of regions, this may cause bias in the measurement results (Kumbhakar, 1990). Therefore, this paper will use the fixed effect SFA model proposed by Greene (2005) to measure technical efficiency (TE) and then use the Malmquist index decomposition method to obtain total factor productivity (TFP), technical change (TPCH), technical efficiency change (TECH). The basic model of SFA-Malmquist with fixed effect is as follows:

$$\ln Y_{it} = lnf\left(X_{it};\beta\right)+\alpha_i+v_{it}-\mu_{it} \quad (1)$$

Here, Y_{it} is the output of province i in t years, X_{it} is the input of i in t years, β is the parameter to be estimated, $f(\cdot)$ is the efficient production function, α_i is the fixed effect of the province, v_{it} is the random error term, and assume that $v_{it} \sim iid\mathcal{N}\left(0,\sigma_v^2\right)$, μ_{it} is the technical inefficiency term. The setting of $f(\cdot)$ has many forms in practical research. The C-D and Translog functions are the most commonly used function forms. To study the accuracy of this paper, the authors employed the LR test. LR test shows that the model in the form of the Translog function is more in line with the data of this paper. Therefore, Formula (1) can be rewritten as follows:

$$\ln Y_{it} = \beta_0+\sum_j \beta_j lnx_{ijt}+t\times\beta_t+\sum_i\sum_l \beta_{jl} lnx_{ijt}\times lnx_{ilt}+t^2\times\beta_{tt}+\sum\beta_{jt} t\times lnx_{ijt}+\alpha_i+v_{it}-\mu_{it} \quad (2)$$

Technical efficiency (TE) can be expressed as:

$$TE_{it} = \exp\left(-\mu_{it}\right), 0\le\exp\left(-\mu_{it}\right)\le 1 \quad (3)$$

According to the formula (3), the change of technical efficiency from t to t + 1 can be calculated and denoted as $TECH_i^{t,t+1}$,

$$TECH_i^{t,t+1} = TE_{i,\ t+1}/TE_{it} \quad (4)$$

The technical change ($TPCH_i^{t,t+1}$) can be derived from the derivation of formula (2). Because under the assumption of non-neutral technical change, technical change will change with the change of input, the technical change value of adjacent periods should be taken as the geometric average value, that is

$$TPCH_i^{t,t+1} = \exp\left(\frac{1}{2}\left(\frac{\partial lnY_{it}}{\partial t}+\frac{\partial lnY_{i,t+1}}{\partial\left(t+1\right)}\right)\right) \quad (5)$$

Considering that most scholars believe that agricultural production conforms to the characteristics of constant returns to scale (Xu et al., 2011), in addition, it is assumed that the TFP obtained under variable returns to scale will be affected by the scale of production (Liu & Meng, 2002). Therefore, under the condition of constant returns to scale, Malmquist index decomposition see formula (6),

$$TFP_i^{t,t+1} = TECH_i^{t,t+1} \times TPCH_i^{t,t+1} \tag{6}$$

3.2. Moran's I Index

Different regions have differences in agricultural TFP due to different resource endowments. However, according to Tobler (1970), "the first law of geography", there is a specific relationship between everything, and with the shortening of distance, this relationship will become closer and closer. (Tobler, 1970) A specific spatial correlation in agricultural TFP may exist. Therefore, testing the spatial correlation of agricultural TFP is crucial. This paper will use the most popular Moran's I to measure the spatial correlation of agricultural TFP in different regions. Moran's I can be expressed as:

$$\mathrm{I} = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}\left(x_i - \overline{x}\right)\left(x_j - \overline{x}\right)}{S^2 \sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}} \tag{7}$$

Where, $S^2 = \frac{\sum_{i=1}^{n}\left(x_i - \overline{x}\right)^2}{n}$ is the variance of the sample, w_{ij} is the spatial weight matrix, and x_i and x_j are the observed values of spatial positions i and j. The value of I is between −1 and 1, greater than 0 indicates positive spatial correlation, less than 0 indicates negative spatial correlation, and equal to 0 indicates no spatial correlation.

In this paper, three spatial weight matrices will be selected, which are geographical adjacency spatial weight matrix (w_1), economic distance spatial weight matrix (w_2) and spatial distance weight matrix (w_3).

Geographical adjacency space weight matrix: $w_1 = w_{ij} = \begin{cases} 1, & i?s\ adjacent\ to\ j \\ 0, & i?s\ not\ adjacent\ to\ j \end{cases}$

Economic distance spatial weight matrix: $w_2 = w_{ij} = \begin{cases} \frac{1}{\left|\overline{Y_i} - \overline{Y_j}\right|}, & i\ is\ adjacent\ to\ j \\ 0,? & i = j \end{cases}$

Spatial distance weight matrix: $w_3 = w_{ij} = \begin{cases} 1/d, & i \neq j \\ 0, & i = j \end{cases}$

Among them, i and j represent region i and region j respectively, $\overline{Y_j}$ represents the average per capita real GDP of region j in the sample interval, and d represents the geographical distance between the provincial capitals of region i and region j.

3.3. Spatial Convergence Model

There are three classical convergence models, σ convergence, β convergence, and club convergence, among which β convergence is the most widely used. β-convergence can be divided into absolute β-convergence and conditional β-convergence. It mainly tests whether the growth rate of inter-provincial agricultural TFP converges. The main difference between absolute β-convergence and conditional β-convergence is that absolute β-convergence assumes that the resource endowments of each region are the same. In contrast, conditional β-convergence considers the differences in resource endowments in different regions, which is more in line with actual production activities (Zhang et al., 2015). Therefore, this paper will use β convergence to test the convergence of agricultural TFP, and compare the difference between absolute β-convergence and conditional β-convergence. The classical conditional β-convergence model is shown in formula (8). If $\sum_{k=1}^{n}\theta_k lnX_{k,i,t}$ is removed, it is absolute β-convergence.

$$\ln TFP_{i,t+1} - \ln TFP_{i,t} = \alpha + \beta \ln TFP_{i,t} + \sum_{k=1}^{n}\theta_k lnX_{k,i,t} + \varepsilon_{i,t} \tag{8}$$

Since the traditional β-convergence model does not consider the spatial influence, the convergence conclusion is biased (Yu, 2015). Therefore, this paper constructs a β-convergence model considering spatial factors and compares the differences between the traditional β-convergence model and the spatial β-convergence model. Since spatial models can be divided into the spatial autoregressive model (SAR), spatial error model (SEM), and spatial Dubin model (SDM), the corresponding β-convergence models considering spatial factors can be divided into the following three types:

The β-convergence model of SAR:

$$ln\frac{TFP_{i,t+1}}{TFP_{i,t}} = \alpha + \rho\sum_{j=1}^{n} w_{ij} ln\frac{TFP_{j,t+1}}{TFP_{j,t}} + \beta \ln TFP_{i,t} + \sum_{k=1}^{n}\theta_k lnX_{k,i,t} + \varepsilon_{i,t} \tag{9}$$

The β-convergence model of SEM:

$$ln\frac{TFP_{i,t+1}}{TFP_{i,t}} = \alpha + \beta \ln TFP_{i,t} + \sum_{k=1}^{n}\theta_k lnX_{k,i,t} + \varphi_{i,t};\ \varphi_{i,t} = \rho\sum_{j=1}^{n} w_{ij}\varphi_{i,t} + \varepsilon_{i,t} \tag{10}$$

The β-convergence model of SDM:

$$ln\frac{TFP_{i,t+1}}{TFP_{i,t}} = \alpha + \rho\sum_{j=1}^{n} w_{ij} ln\frac{TFP_{j,t+1}}{TFP_{j,t}} + \beta \ln TFP_{i,t} + \sum_{k=1}^{n}\theta_k lnX_{k,i,t} + \varnothing_k \sum_{j=1,k=1}^{n} w_{ij} lnX_{k,i,t} + \varepsilon_{i,t} \tag{11}$$

Among them, $TFP_{i,t}$ and $TFP_{i,t+1}$ are the agricultural TFP of province i in period t and period $t+1$, respectively, and β is the convergence judgment coefficient. If β is significantly negative, it indicates convergence, and the convergence speed ω can be calculated according to $\beta = -(1-e^{-\omega T})/\mathrm{T}$. θ_k is the estimated coefficient of the control variable $X_{i,t}$. When $\theta_k = 0$, it is absolute β-convergence. Otherwise, it is conditional β-convergence. $\varepsilon_{i,t}$ is a random error term and is assumed to satisfy $\varepsilon_{i,t} \sim iid\left(0,\sigma^2\right)$. ρ is the spatial auto-regressive coefficient, $\varphi_{i,t}$ is the error term of spatial autocorrelation, and $\varnothing_k$ is the regression coefficient of the interaction effect between the control variable and the spatial weight matrix. w_{ij} is the spatial weight matrix.

4. Index Selection and Data Sources

To conduct in-depth research on China's agricultural total factor productivity, the starting year of this study was selected as 1978, and all data were from the "China Statistical Yearbook", "China Rural Statistical Yearbook", "New China 50 Years Statistical Data Compilation". Considering the problem of merging Sichuan and Chongqing before, Chongqing is classified into Sichuan. Hainan, and Tibet, not within the scope of this study due to the lack of data. This paper finally obtains the panel data of 28 provinces and cities from 1978 to 2020 for 43 years.

In constructing the input-output index system for measuring agricultural TFP, this paper refers to the general treatment method of the existing literature (Gong, 2018a; Shi et al., 2016). It selects the number of employees in agriculture, forestry, animal husbandry, and fishery (ten thousand people), the sown area of crops (thousand hectares), the total power of agricultural machinery (ten thousand kilowatts), and the application amount of agricultural fertilizer (ten thousand tons) to represent the labor input, land input, capital input and intermediate input in the process of agricultural production, respectively. Taking the total output value of agriculture, forestry, animal husbandry, and fishery (billion yuan) as output and conducted price index deflations based on the 1978.

By studying the existing literature on the selection of influencing factors of agricultural TFP and considering data availability. This paper selects the proportion of the affected area of crops to the affected area (Gong, 2018a), based on the per capita GDP after the deflator in 1978 (Zhang & Chen, 2015), the proportion of the urban resident population to the total population (Yang et al., 2017), the proportion of the total highway mileage to the land area of the province (Zhuo & Zeng, 2018), the proportion of the added value of the secondary industry to the GDP (Wang & Zhang, 2018), and the proportion of the effective irrigation area to the sown area of crops (Gong, 2018a), representing the disaster situation (Disas), economic development (Gdppc), urbanization level (Citil), transportation convenience (Trans), the development of the secondary industry (Indus) and irrigation level (Irrig). A total of 6 variables are used as the driving factors affecting the spatial and temporal changes of agricultural TFP.

5. Empirical Results and Analysis

5.1. The Measurement and Timing Analysis of China's Agricultural TFP

Before measuring the TFP of agriculture, this paper first analyzes the input-output data of provincial agricultural production from 1978 to 2020. The first two lines of Table 1 show the annual agricultural input-output level in 1978 and 2020. The last six lines show the agricultural input-output's average annual growth rate in different agricultural development stages. The total agricultural output value continued to increase throughout the study period, with an average annual growth rate of more than 4 %. Regarding input factors, the input of land, fertilizer, and machinery has shown an increasing trend. Only the labor input has shown a decreasing trend in individual stages. This is mainly due to the advancement of urbanization and industrialization. The large-scale transfer of rural surplus labor to the city has reduced the labor engaged in agricultural production.

Table 1. Input and output of agricultural production.

		Total Agricultural Output Value	Labour	Land	Fertilizer	Mechanics
		Billion Yuan	Ten Thousand People	Hectares	10000 Tons	10000 Kilowatts
Annual Value	1978	1397	28318	146379	884	11749.9
	2020	137782.2	17715	167487	5250.7	105622.1
Average Annual Growth Rate	1978–1984	6.9%	2.1%	9.4%	11.8%	9.4%
	1985–1989	6.2%	−0.4%	7.4%	7.4%	7.4%
	1990–1993	5.5%	0.6%	3.2%	7.5%	3.2%
	1994–1998	7.6%	0.3%	5.6%	5.9%	5.6%
	1999–2003	4.7%	−0.7%	5.1%	1.3%	5.1%
	2004–2020	4.5%	−1.0%	3.6%	1.9%	3.6%

Note: According to Gong (2018a)' s division of agricultural production stages, China's agricultural development since 1978 can be divided into six stages, namely, the transition period from a collective economy to a family-based agricultural system from 1978 to 1984, the dual-track system period from 1985 to 1989, the in-depth reform stage of the joint procurement and marketing system from 1990 to 1993, the tax and fee system reform stage from 1994 to 1998, the comprehensive economic reform period of rural development from 1999 to 2003, and the focus on the development period of agriculture, rural areas, and farmers from 2004 to the present.

The agricultural TFP of 28 provinces for 42 years from 1979 to 2020 was calculated using the fixed effects SFA Malmquist model in Stata software. It analyzes the development trend of China's agricultural TFP since 1979. Figure 1 shows the average annual growth rate of China's agricultural TFP. By observing the figure, it can be found that the Malmquist productivity index calculated each year is greater than 1, indicating that the TFP of China's agriculture has shown a growing trend in the past four decades. However, over time, the growth rate of agricultural TFP gradually slowed down, especially since 1993, the average annual growth rate of TFP began to decline, which also verified the previous research conclusions, that is, from the 1990s, the growth rate of China's agricultural TFP slowed down (Chen et al., 2008; Zhou & Zhang, 2013).

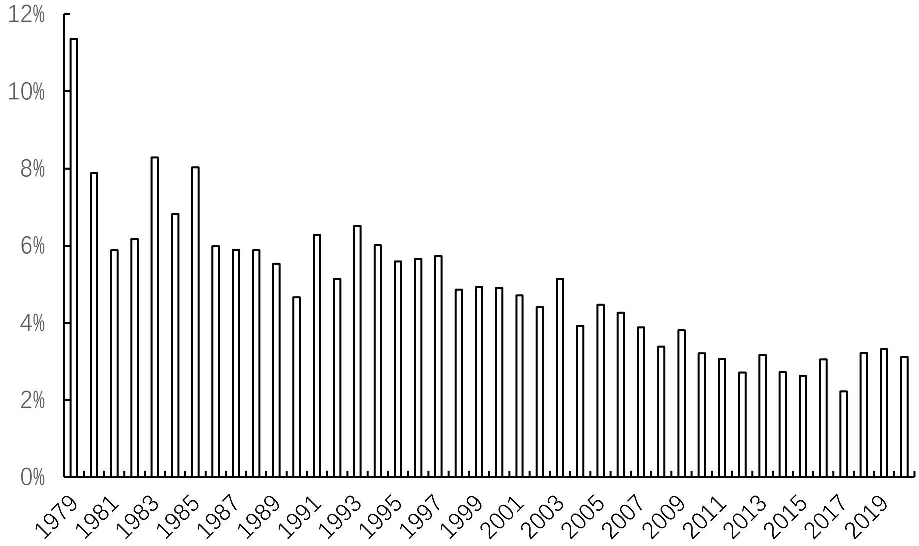

Figure 1. Annual growth rate of agricultural total factor productivity in China.

To further analyze the changing trend of China's agricultural TFP growth before and after the 1990s and the difference of agricultural TFP in different regions, figure 2 lists the changing trend of agricultural TFP growth in three stages (1979–2020,1979–1990 and 1991–2020) and three regions (eastern, central and western). First, agricultural TFP growth in 1979–1990 was significantly higher than in 1991–2020 and 1979–2020, further verifying the previous conclusions. Although the growth rate of China's agricultural TFP slowed down after the 1990s, it is still growing, which shows that a series of agricultural reforms and agricultural support policies implemented since 1979 have effectively promoted the improvement of agricultural TFP. Secondly, by comparing the growth of agricultural TFP in the three regions of the Middle, East, and West, it can be found that the Eastern region is the highest, which shows that the agricultural technology level in the Eastern region has made significant progress, and attaches great importance to scientific and technological innovation in the process of agricultural production. The low growth of TFP in the central and western regions shows that the above two regions rely too much on the initial factor input in agricultural production. The role of agricultural science and technology innovation in agricultural production is relatively small, and agricultural production is still in a relatively extensive state.

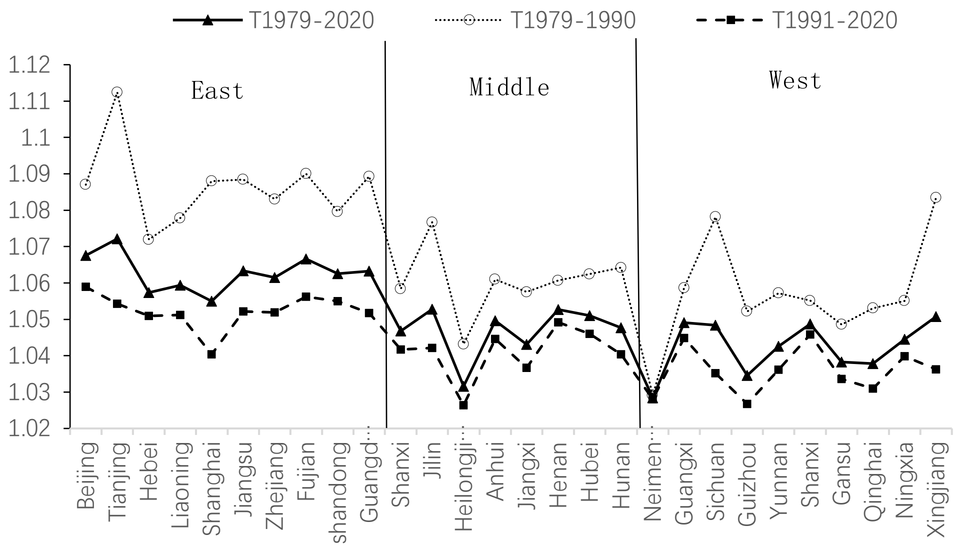

Figure 2. Growth and changing trend of agricultural total factor productivity in China.

The above analysis shows that China's agricultural TFP has been growing since 1979. What is the reason for the growth of TFP? According to Equations (4), (5), and (6), the growth of TFP can be decomposed into technological progress (TPCH) and changes in technical efficiency (TECH), and the factor decomposition diagram of TFP growth since 1978 is obtained. It can be seen from Figure 3 that the value of technical progress (TPCH) is all greater than 1, and some values of Technical Efficiency Change (TECH) are less than 1. This shows that the growth of China's agricultural total factor productivity mainly depends on the progress of agricultural technology. In contrast, technical efficiency sometimes plays the opposite role, which to some extent offsets the effect of the improvement of agricultural technology level. Further analysis of the trend of technological progress and technical efficiency changes before and after 1990 shows that after the 1990s, the growth rate of technological progress began to slow down, and the growth rate of technical efficiency showed a slow upward trend, indicating that the impact of technical efficiency on agricultural total factor productivity began to strengthen gradually.

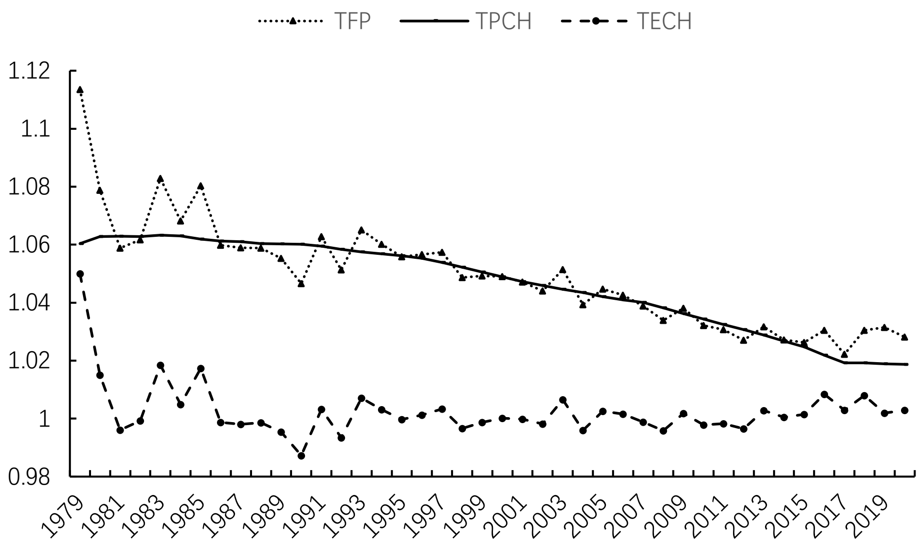

Figure 3. Decomposition of China's agricultural total factor productivity growth from 1979 to 2020.

5.2. Spatial Correlation Analysis of Agricultural TFP in China

To test whether there is a spatial correlation in the TFP of agricultural production, Table 2 lists the global Moran's I calculated based on the geographical adjacency spatial weight matrix. The results show that Moran's I index from 1985 to 2020 is between 0.21 and 0.47. Both are significant at the 5 % significance level, indicating a spatial correlation in the TFP of agriculture in various provinces and cities in China. In addition, this spatial correlation is becoming increasingly obvious over time. This phenomenon may be due to the flow of agricultural production factors between regions, the promotion of agricultural technology extension projects, and mechanical cross-regional operations (Gao & Song, 2014). Notably, the TFP of 1978–1984 did not pass the global correlation test. Further, it is necessary to examine the local spatial correlation of the above years through local Moran's I. Table 3 lists the LISA clustering results for insignificant years. Table 3 shows that although there was no global correlation between 1979 and 1984, there is a specific regional accumulation in the local area, reflecting the imbalance of agricultural development in China to a certain extent. This paper also uses the economic distance spatial weight matrix and the geospatial distance weight matrix to measure the spatial correlation of agricultural TFP in each province and city. The results are very similar to Table 2 and Table 3. Due to the length of the article, it is not shown here.

Table 2. Moran's I index of agricultural total factor productivity from 1979 to 2020.

Year	Moran's I	P-value	Year	Moran's I	P-value
1979	0.087	0.314	2000	0.400	0.000
1980	0.105	0.238	2001	0.427	0.000
1981	0.073	0.336	2002	0.441	0.000
1982	0.051	0.465	2003	0.447	0.000
1983	0.112	0.205	2004	0.449	0.000
1984	0.150	0.126	2005	0.454	0.000
1985	0.210	0.039	2006	0.454	0.000
1986	0.233	0.025	2007	0.460	0.000
1987	0.239	0.022	2008	0.464	0.000
1988	0.271	0.012	2009	0.466	0.000
1989	0.289	0.008	2010	0.470	0.000
1990	0.329	0.003	2011	0.473	0.000
1991	0.305	0.005	2012	0.472	0.000
1992	0.311	0.005	2013	0.478	0.000
1993	0.343	0.002	2014	0.483	0.000
1994	0.351	0.002	2015	0.486	0.000
1995	0.375	0.001	2016	0.482	0.000
1996	0.384	0.001	2017	0.470	0.000
1997	0.376	0.001	2018	0.479	0.000
1998	0.382	0.001	2019	0.483	0.000
1999	0.366	0.001	2020	0.476	0.000

Table 3. LISA clustering results in insignificant years.

	H-H	L-L	H-L	L-H
1979		Shanxi, Shaanxi	Sichuan	
1980		Shaanxi, Gansu, Ningxia	Sichuan, Xinjiang	
1981		Shanxi, Shaanxi, Ningxia	Jilin	NeiMongol
1982		Shanxi., Shaanxi, Gansu, Ningxia	Jilin, Sichuan, Xinjiang	NeiMongol
1983		NeiMongol, Shaanxi, Gansu, Ningxia	Xinjiang	
1984	Tianjin	Shanxi, NeiMongol, Shaanxi, Gansu, Ningxia	Sichuan, Xinjiang	

Note: H-H represents high value surrounded by high value, L-L represents low value surrounded by low value, H-L represents high value surrounded by low value, and L-H represents low value surrounded by high value.

5.3. Convergence Analysis of Agricultural Total Factor Productivity in China

For the traditional β-convergence model, the Hausman test is first carried out to determine that the fixed effect should be selected to analyze the convergence of China's agricultural TFP. As mentioned, China's agricultural TFP has a spatial correlation. Based on three spatial econometric models, three spatial β-convergence models (SAR spatial β-convergence model, SEM spatial β-convergence model, and SDM spatial β-convergence model) are constructed. According to the Wald test, the SDM spatial β-convergence model is optimal, and the spatial Hausman test results still support the fixed effect.

It can be seen from Table 4 that the coefficients of $lnTFP_{i,t}$ in all models are significantly negative, which indicates that there is an apparent convergence trend in China's agricultural total factor productivity and the gap between regional agricultural total factor productivity is shrinking. Through comparing the traditional absolute convergence and conditional convergence, the study found that the convergence speed of conditional convergence (0.065) is greater than that of absolute convergence (0.049). The same conclusion can be drawn by comparing spatial absolute and spatial conditional convergence. That is, the convergence speed of spatial conditional convergence (0.088) is greater than that of spatial absolute convergence (0.074). This is because conditional convergence considers the differences in production factors between regions, shortens the period of convergence, and makes the convergence test closer to reality; Spatial factors have the effect of accelerating convergence. By comparing the convergence speed of the three models of spatial absolute β-convergence and spatial conditional β-convergence, it can be found that the convergence speed of SAR, SEM, and SDM with spatial conditional β-convergence is significantly faster than that of spatial absolute β-convergence. This phenomenon may be because the spatial spillover effect or diffusion effect narrows the inter-regional agricultural production gap, thus accelerating the convergence speed. For the control variables, the direction and significance level of the influence of the coefficients of the traditional convergence model and the spatial convergence model on the TFP of agriculture is the same. There are some differences in the size of the coefficients. Because the control variables are not the focus of this study, they are not explicitly analyzed.

Table 4. The β convergence of agricultural total factor productivity in China.

Variable	Traditional Absolute β-convergence	Spatial Absolute β-convergence			Traditional Conditional β-convergence	Spatial Conditional β-convergence		
		SAR	SEM	SDM		SAR	SEM	SDM
$lnTFP_{i,t}$	−0.048***	-0.047***	-0.052***	-0.071***	−0.063***	-0.061***	-0.065***	-0.077***
	(0.011)	(0.005)	(0.005)	(0.007)	(0.015)	(0.006)	(0.006)	(0.007)
Trans					0.010	0.010***	0.010**	−0.006
					(0.006)	(0.004)	(0.004)	(0.006)
Citil					0.003	0.003	0.003	0.004
					(0.003)	(0.004)	(0.004)	(0.004)
Irrig					0.018	0.019	0.019	0.012
					(0.020)	(0.013)	(0.013)	(0.014)
Disas					0.001	0.001	0.001	0.001
					(0.006)	(0.005)	(0.005)	(0.005)
Indus					−0.016	−0.016	−0.019	−0.030*
					(0.026)	(0.015)	(0.015)	(0.016)
$\ln\left(\text{Gdppc}\right)$					0.023***	0.022***	0.023***	0.022***
					(0.006)	(0.005)	(0.005)	(0.005)
Constant	0.114***				−0.048			
	(0.022)				(0.036)			
Rho		0.104**	0.145***	0.145***		0.098**	0.129***	0.140***
		(0.040)	(0.041)	(0.041)		(0.040)	(0.041)	(0.041)
R-squared	0.468	0.154	0.146	0.031	0.484	0.095	0.095	0.188
Convergence Rate	0.049	0.048	0.053	0.074	0.065	0.063	0.067	0.080
Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Based on analyzing the influence of spatial effect on the convergence of China's agricultural total factor productivity, the following will further study the spatial convergence characteristics of China's agricultural total factor productivity by period (before and after the 1990s), by region (eastern, central and western) and by using different spatial weight matrices (geographical adjacency spatial weight matrix w_1, economic distance spatial weight matrix w_2 and spatial distance weight matrix w_3).

Table 5 reports the regression results of the SDM conditional β-convergence model with fixed effects in different periods. On the whole, the results of each convergence model with different spatial weight matrices in different periods show that China's agricultural TFP has the characteristics of convergence, which also shows that the convergence trend of China's agricultural TFP is robust; The convergence rate of China's agricultural TFP shows a decreasing trend. The convergence rate between 1979–1990 is significantly higher than between 1991–2020. This may be due to the lack of production resources in the early stage of reform and opening up. The agricultural production conditions in various regions vary considerably. With the reform and opening up, the flow rate of agricultural production factors between regions continues to increase. Agricultural production in various regions has released great potential, and inefficient regions are growing faster. However, with the deepening of the reform, the gap in resource endowments between regions has gradually narrowed, the conditions for agricultural production have been continuously improved, and agriculture has been continuously transformed from 'quantity growth' to 'quality growth', which has slowed down the convergence rate to a certain extent.

Table 5. Conditional β convergence of agricultural total factor productivity in different periods based on SDM.

Variable	1979–1990			1991–2020			1979–2020		
	w_1	w_2	w_3	w_1	w_2	w_3	w_1	w_2	w_3
$lnTFP_{i,t}$	−0.377***	−0.415***	−0.338***	−0.032***	−0.030***	−0.025***	−0.077***	−0.067***	−0.063***
	(0.025)	(0.029)	(0.026)	(0.008)	(0.007)	(0.007)	(0.007)	(0.007)	(0.006)
Rho	0.161**	−0.159**	0.120	0.283***	−0.128**	0.252**	0.140***	−0.132***	0.182*
	(0.071)	(0.077)	(0.183)	(0.048)	(0.054)	(0.107)	(0.041)	(0.045)	(0.094)
R-squared	0.260	0.214	0.161	0.059	0.188	0.217	0.188	0.159	0.025
Convergence Rate	0.473	0.536	0.412	0.033	0.030	0.025	0.080	0.069	0.065
Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: The control variables are the disaster situation (Disas), economic development (Gdppc), urbanization level (Citil), transportation convenience (Trans), secondary industry development (Indus), and irrigation level (Irrig) mentioned above.

Table 6 reports the regression results of the conditional β-convergence model of SDM with fixed effects in different regions. Overall, the convergence model results of different regions and spatial weight matrices show that China's agricultural TFP has convergence characteristics. The convergence speed of China's agricultural TFP shows a spatial distribution pattern decreasing in the western, eastern, and central regions. The western region has the fastest convergence rate. The possible reason is that the western region is rich in agricultural resources. Still, the social and economic development level is low, and the level of agricultural production technology is relatively low. However, with the advancement of the Western development strategy, the Western region has developed rapidly. The acceleration of inter-regional resource and technology flow has shortened the convergence cycle of agricultural TFP. The central region is primarily the prominent grain-producing area, the agricultural production conditions are relatively perfect, and the overall level of agricultural production technology is relatively high. Although the eastern region is economically developed, agricultural production is not its primary goal. The marginal effect of technology and capital investment in the central and eastern regions is decreasing, and the convergence rate of agricultural TFP is slow.

Table 6. Conditional β convergence of agricultural total factor productivity in different areas based on SDM.

Variable	Eastern			Central			Western		
	W_1	W_2	W_3	W_1	W_2	W_3	W_1	W_2	W_3
$lnTFP_{i,t}$	−0.125***	−0.174***	−0.093***	−0.098***	−0.172***	−0.145***	−0.192***	−0.096***	−0.282***
	(0.022)	(0.027)	(0.025)	(0.022)	(0.029)	(0.029)	(0.017)	(0.013)	(0.025)
Rho	−0.094	−0.761***	−0.569***	−0.288***	−0.230***	−0.191**	−0.487***	−0.221***	−0.932***
	(0.061)	(0.083)	(0.118)	(0.048)	(0.079)	(0.088)	(0.076)	(0.069)	(0.148)
R-squared	0.350	0.433	0.367	0.217	0.161	0.267	0.207	0.099	0.232
Convergence Rate	0.134	0.191	0.098	0.103	0.189	0.157	0.213	0.101	0.331
Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: The control variables are the disaster situation (Disas), economic development (Gdppc), urbanization level (Citil), transportation convenience (Trans), secondary industry development (Indus), and irrigation level (Irrig) mentioned above.

6. Conclusions and Policy Recommendations

With the improvement of China's agricultural market and the continuous improvement of regional openness and communication, the flow of agricultural production factors among regions is becoming increasingly frequent. Spatial factors have become a non-negligible factor affecting the change in China's agricultural TFP. This paper takes the provincial panel data from 1978 to 2020 as the research object, uses the fixed effect SFA-Malmquist model to measure each province and city's agricultural TFP, and determines the spatial correlation of China's agricultural TFP through Moran's I. On this basis, the spatial factors are included in the β-convergence model. The spatial convergence characteristics of China's agricultural TFP are analyzed in different periods and regions. Through analysis, the following main conclusions are obtained:

First, since 1978, the TFP of China's agriculture has shown a growing trend, but its growth rate has gradually slowed over time. This conclusion is consistent with the research results of Chen et al., (2008) and Zhou and Zhang (2013). Comparing the growth of agricultural TFP in the central, eastern, and western regions, it can be found that the eastern region has the highest TFP growth. In contrast, the central and western regions have lower TFP growth. The growth of agricultural TFP in China mainly depends on the progress of agricultural technology. Still, the impact of technical efficiency on agricultural TFP has gradually strengthened.

Second, China's agricultural TFP has significant spatial correlation and spatial convergence characteristics. The differences in agricultural TFP in various regions are shrinking over time, and the spatial spillover effect significantly shortens the convergence process. By studying the convergence process in different periods, it is found that the convergence speed between 1979 and 1990 is significantly higher than that between 1991 and 2020. By studying the convergence process in different regions, it is found that the convergence speed of China's agricultural TFP shows a spatial distribution pattern of decreasing in the west, east, and middle.

Practical implications of this research include:

First, China's agricultural TFP still has a lot of room for improvement. In the future, the use of digital technology, advanced equipment, and other means will continue to improve technical efficiency to achieve the growth of China's agricultural TFP. In recent years, digital technology and digital equipment have been gradually applied to the agricultural field, and smart agriculture and digital agriculture have also been continuously promoted everywhere, which will effectively improve China's agricultural TFP. In the future, efforts should be made to continuously promote digital technology, advanced equipment, and other technologies in the agricultural field.

Second, while strengthening its own agricultural production, the regional government should also take complete account of the advantages of agricultural resources in neighboring regions, strengthen cooperation and exchanges between regions, and constantly play the spillover effect of regions with high agricultural TFP. This paper has proved that China's agricultural TFP has significant spatial agglomeration specificity and spatial effect, which benefits from the flow of production factors, technology, personnel, etc., among regions. In the future, based on constantly strengthening cooperation and exchange between regions, we should give full play to the role of digital technology, break down barriers between regions, and promote the entire flow of technology, personnel, and factors to achieve the goal of jointly improving agricultural TFP.

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References

Caves, D., Christensen, L., & Diewert, W. (1982). The economic theory of index numbers and the measurement of input, output, and productivity. *Econometrica: Journal of the Econometric Society*, 1393–1414.
Chen, P., Yu, M., Chang, C., & Hsu, S. (2008). Total factor productivity growth in China's agricultural sector. *China Economic Review*, *19*(4), 580–593. https://doi.org/10.1016/j.chieco.2008.07.001
Fan, L., & Li, G. (2012). Total factor productivity and its research progress in the field of agriculture. *Modern Economic Science*, *34*(1), 109–119+128.
Gao, F. (2015). Evolution trend and internal mechanism of regional total factor productivity in Chinese agriculture. *The Journal of Quantitative & Technical Economics*, *32*(5), 3–19+53. https://doi.org/10.13653/j.cnki.jqte.2015.05.001
Gao, M., & Song, H. (2014). The spatial convergence of grain production technical efficiency and the difference of functional areas also on the spatial ripple effect of technology diffusion. *Management World*, (7), 83–92. https://doi.org/10.19744/j.cnki.11-1235/f.2014.07.010
Gao, M., Song, H., & Carter, M. (2016). The impact of grain direct subsidies on wheat productivity of farmers with different scales of operation based on data of rural households in fixed observation points nationwide. *Chinese Rural Economy*, (8), 56–69.
Gong, B. (2018a). Agricultural reforms and production in China: Changes in provincial production function and productivity in 1978–2015. *Journal of Development Economics*, *132*, 18–31. https://doi.org/10.1016/j.jdeveco.2017.12.005
Gong, B. (2018b). The contribution of inputs and productivity to agricultural growth in China. *Journal of Agrotechnical Economics*, (6), 4–18. https://doi.org/10.13246/j.cnki.jae.2018.06.001
Greene, W. (2005). Reconsidering heterogeneity in panel data estimators of the stochastic frontier model. *Journal of Econometrics*, *126*(2), 269–303. https://doi.org/10.1016/j.jeconom.2004.05.003
Hou, M., & Yao, S. (2018). Spatial-temporal evolution and trend prediction of agricultural eco-efficiency in China: 1978–2016. *Acta Geographica Sinica*, *73*(11), 2168–2183. https://doi.org/10.11821/dlxb201811009
Huo, Z., Wu, Y., & Zhou, Z. (2011). Evaluation of agricultural productivity China based on input-output. *Economic Geography*, *31*(6), 999–1002.
Jia, L., & Xia, Y. (2017). Scale efficiency of grain production and influencing factors based on survey data from Heilongjiang, Henan and Sichuan. *Resources Science*, *39*(5), 924–933. https://doi.org/10.18402/resci.2017.05.12
Kuang, Y. (2012). Technology efficiency, technology progress, factor accumulation and China's agricultural economic growth. *The Journal of Quantitative & Technical Economics*, *29*(1), 3–18. https://doi.org/10.13653/j.cnki.jqte.2012.01.009
Kumbhakar, S. (1990). Production frontiers, panel data, and time-varying technical inefficiency. *Journal of Econometrics*, *46*(1–2), 201–211. https://doi.org/10.1016/0304-4076(90)90055-X
Li, G. (2014). The green productivity revolution of agriculture in China from 1978 to 2008. *China Economic Quarterly*, *13*(2), 537–558. https://doi.org/10.13821/j.cnki.ceq.2014.02.011
Li, S., & Yin, X. (2017). Analysis of the impact of rural labor transfer on agricultural total factor productivity in China. *Journal of Agrotechnical Economics*, (9), 4–13. https://doi.org/10.13246/j.cnki.jae.2017.09.001
Lin, J. (1992). Rural reforms and agricultural growth in China. *The American Economic Review*, 34–51.
Liu, Y., & Meng, L. (2002). SFA method for measuring Malmquist productivity index. *Journal of Beijing Institute of Technology (Social Sciences Edition)*, (S1), 42–44.
Nin Pratt, A., Yu, B., & Fan, S. (2008). The total factor productivity in China and India: New measures and approaches. *China Agricultural Economic Review*, *1*(1), 9–22. https://doi.org/10.1108/17561370910915339
Pan, D., & Ying, R. (2012). Spatial-temporal differences of agricultural total factor productivity: Restudy of previous literatures. *Economic Geography*, *32*(7), 113–117+128. https://doi.org/10.15957/j.cnki.jjdl.2012.07.018
Quan, J. (2009). Empirical analysis of China's agricultural total factor productivity growth: 1978 ~ 2007-Based on Stochastic Frontier Analysis (SFA) method. *Chinese Rural Economy*, (9), 36–47.
Shi, C., Zhu, J., & Jie, C. (2016). Regional differences and convergence analysis of agricultural total factor productivity growth in China-based on fixed effect SFA model and panel unit root method. *Inquiry Into Economic Issues*, (4), 134–141.
Tobler, W. (1970). A computer movie simulating urban growth in the Detroit region. *Economic Geography*, *46*, 234–240.
Wang, B., & Zhang, W. (2018). Cross-provincial differences in determinants of agricultural eco-efficiency in China: An analysis based on panel data from 31 provinces in 1996-2015. *Chinese Rural Economy*, (1), 46–62.
Wang, S., Tuan, F., Gale, F., Somwaru, A., & Hansen, J. (2013). China's regional agricultural productivity growth in 1985–2007: A multilateral comparison. *Agricultural Economics*, *44*(2), 241–251. https://doi.org/10.1111/agec.12008
Wang, Y., Song, W., & Han, X. (2010). Spatial econometric analysis of agricultural total factor productivity and its influencing factors in China-Based on provincial spatial panel data from 1992 to 2007. *Chinese Rural Economy*, (8), 24–35.
Wu, S., Walker, D., Devadoss, S., & Lu, Y. (2001). Productivity growth and its components in Chinese agriculture after reforms. *Review of Development Economics*, *5*(3), 375–391. https://doi.org/10.1111/1467-9361.00130

Wu, Y. (2010). An estimation of output elasticity of regional agricultural production factors in China—An empirical study with spatial econometric models. *Chinese Rural Economy*, (6), 25-37+48.
Xu, Q., Yin, R., & Zhang, H. (2011). Economies of scale, returns to scale and the problem of optimum-scale farm management: An empirical study based on grain production in China. *Economic Research Journal*, *46*(3), 59–71+94.
Xu, Y. (1999). Agricultural productivity in China. *China Economic Review*, *10*(2), 108–121.
Yang, G., & Yang, M. (2013). The spatial correlation effect of agricultural total factor productivity in China—An empirical study based on static and dynamic spatial panel models. *Economic Geography*, *33*(11), 122–129.
Yang, Y., Lin, W., & Zhang, L. (2017). Agricultural technology progress, technical efficiency and grain production—An empirical analysis based on provincial panel data in China. *Journal of Agrotechnical Economics*, (5), 46–56. https://doi.org/10.13246/j.cnki.jae.2017.05.005
Yu, Y. (2015). Research on the dynamic spatial convergence of provincial total factor productivity in China. *The Journal of World Economy*, *38*(10), 30–55. https://doi.org/10.19985/j.cnki.cassjwe.2015.10.003
Zeng, Y., Lv, Y., & Wang, X. (2018). Multidimensional analysis of the impact of farmland transfer on the technical efficiency of grain production—An empirical study based on stochastic frontier production function. *Journal of Huazhong Agricultural University (Social Sciences Edition)*, (1), 13–21+156–157. https://doi.org/10.13300/j.cnki.hnwkxb.2018.01.002
Zhang, L., & Cao, J. (2013). China's agricultural total factor productivity growth: The introduction of allocative efficiency change—An empirical analysis based on stochastic frontier production function method. *Chinese Rural Economy*, (3), 4–15.
Zhang, L., & Chen, S. (2015). Empirical Analysis on spatial-temporal evolution and driving forces of per capita grain possession in China. *Economic Geography*, *35*(3), 171–177. https://doi.org/10.15957/j.cnki.jjdl.2015.03.025
Zhang, Z., Xue, B., Chen, X., & Li, Y. (2015). Convergence in spatial difference of industrial environmental efficiency in China. *China Population Resources and Environment*, *25*(2), 30–38. https://doi.org/10.3969/j.issn.1002-2104.2015.02.005
Zhou, L., & Zhang, H. (2013). Productivity growth in China's agriculture during 1985–2010. *Journal of Integrative Agriculture*, *12*(10), 1896–1904. https://doi.org/10.1016/S2095-3119(13)60598-5
Zhuo, L., & Zeng, F. (2018). Research on the impact of rural infrastructure on total factor productivity of grain. *Journal of Agrotechnical Economics*, (11), 92–101. https://doi.org/10.13246/j.cnki.jae.2018.11.007