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CROP PRODUCTION

Spatiotemporal differentiation and spatial correlation of agricultural total factor productivity in China: an estimation based on the data of prefecture-level cities

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ABSTRACT: *The improvement of agricultural TFP is critical to promoting the high-quality development of agriculture. This paper described and identified the spatiotemporal differentiation characteristics and spatial correlation of China's agricultural TFP in 283 prefecture-level cities from 2001 to 2018 using the Metafroniter-Malmquist and Moran index. The results showed that: (1) From 2001 to 2018, China's agricultural TFP was 6.64%, and its growth was mainly driven by agricultural technological progress. The contribution of agricultural technological efficiency was small. The growth law showed an "inverted U-shaped" growth trend of first rising and then falling. (2) China's agricultural TFP has significant characteristics of regional unbalanced growth. (3) The growth rate of agricultural TFP in most prefecture-level cities is medium and slow, and most prefecture-level cities relied on agricultural technological progress to promote growth. (4) The agricultural TFP of various cities showed a significant spatial correlation phenomenon of "high-high" or "low-low." This study has significant theoretical and practical value for maintaining the stable growth of China's agricultural TFP and promoting the high-quality development of China's agriculture.*

Key words: *agricultural total factor productivity, spatiotemporal differentiation, spatial correlation, Metafrontier-Malmquist index, Moran index, prefecture-level cities.*

Diferenciação espaço-temporal e correlação espacial da produtividade fatorial total agrícola na China: uma estimativa baseada em dados de cidades em nível de prefeitura

RESUMO: *A melhoria do TFP agrícola é fundamental para promover o desenvolvimento de alta qualidade da agricultura. Este artigo descreve e identifica as características de diferenciação espaço-temporal e a correlação espacial do TFP agrícola chinês em 283 cidades de nível de prefeitura, de 2001 a 2018, usando os índices Metafroniter-Malmquist e Moran. Os resultados mostram que: (1) De 2001 a 2018, o TFP agrícola da China foi de 6,64%, e seu crescimento foi impulsionado principalmente pelo progresso tecnológico agrícola. A contribuição da eficiência tecnológica agrícola foi pequena. A lei de crescimento mostrou uma tendência de crescimento "em forma de U invertido" de primeiro aumento e depois queda. (2) O TFP agrícola chinês apresenta características significativas de crescimento desequilibrado regional. (3) A taxa de crescimento do TFP agrícola na maioria das cidades de nível de prefeitura é média e lenta, e a maioria das cidades de nível de prefeitura depende do progresso tecnológico agrícola para promover o crescimento. (4) O TFP agrícola de várias cidades apresentou um fenômeno de correlação espacial significativo de "alto-alto" ou "baixo-baixo". Este estudo tem valor teórico e prático significativo para manter o crescimento estável do TFP agrícola da China e promover o desenvolvimento de alta qualidade da agricultura da China.*

Palavras-chave: *produtividade fatorial total agrícola, diferenciação espaço-temporal, correlação espacial, indice Metafronteira-Malmquist, Índice de Moran, cidades a nível da província.*

INTRODUCTION

Agricultural total factor productivity (TFP) is an essential issue in Agricultural Economics and Development Economics, which significantly impacts a country's agricultural production, industrial and service industry development, and economic structure transformation (WANG et al., 2020). Improving agricultural TFP can promote the growth of agricultural production, release the rural surplus labor force to participate in industry, and promote the development of industrial and service industry (CAO & BIRCHENALL, 2013). In addition, with the current transformation of China's economy from a high-speed growth stage to a high-quality development stage, the transformation of China's agriculture to

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high-quality development has become an inevitable trend. Improving agricultural TFP is also critical to achieving high-quality agricultural development (PENG et al., 2019). Therefore, it is significant to measure and study China's agriculture TFP.

The existing methods to measure TFP mainly include Stochastic Frontier Analysis (SFA) and Data Envelopment Analysis (DEA). As a typical parameter analysis method, the SFA model needs to set up the specific production function form and the probability distribution of error terms. On this basis, the production efficiency of the sample is calculated according to the frontier of the production function (KUMBHAKAR et al., 2015). However, the SFA model needs to make strict assumptions about the production function. If there are errors in the setting of the production function, the estimated results will deviate from the actual situation (AIGNER et al., 1977; LIN & WANG, 2014). Therefore, the SFA model is not the best way to measure agricultural TFP (LIU et al., 2021). As a non-parametric analysis method, the advantage of DEA is that it uses a linear programming method to estimate the objective function to evaluate the efficiency of the Decision-Making Unit (DMU) with multiple inputs and outputs (WANG et al., 2019a). Moreover, the production process of multiple inputs and multiple outputs can be simulated without setting a strict production function (GUO et al., 2018). Therefore, when measuring agricultural TFP, it is favored by scholars.

Among many DEA models, the Malmquist index based on DEA is one of the critical methods to measure the TFP index. FARE et al. (1992) first used the DEA method to calculate the Malmquist index and decomposed the Malmquist index into two aspects: the change in technical efficiency and the change in production technology. Since then, scholars have primarily used Malmquist index to calculate the productivity index. For example, UMETSU et al. (2003) used the Malmquist index to measure the TFP of rice production in the Philippines and its change law. They decomposed TFP into technical efficiency and technical change based on calculation. COELLI & RAO (2005) used the Malmquist index to calculate the agricultural TFP and its change trend in 93 countries in the world, which accounted for the central part of the world's population and agricultural output. TIPI & REHBER (2006) used the Malmquist index to measure the agricultural technical efficiency and TFP of the South Marmara Region in Turkey from 1993 to 2002. ARMAGAN et al. (2010) used the Malmquist index to calculate the TFP of crop production in Turkey, and they considered significant regional differences in the TFP of crop production in Turkey.

With the development of China's agriculture, the measurement of agricultural TFP has become an essential object for scholars. At present, scholars mainly use the following two types of data to measure China's agriculture TFP: the first kind of research usually uses macro data at the provincial-level to measure and analyze the evolution trend of China's agricultural TFP (JIN et al., 2009; SONG et al., 2016; HAN et al., 2018; WANG et al., 2019a; WANG et al., 2019b; XU et al., 2019; FENG et al., 2020 LIU et al., 2020c). However, due to China's vast land area and numerous provincial administrative regions, there is significant regional heterogeneity in agricultural production activities within each province (LI et al., 2020). Suppose we measure China's agricultural TFP from the provincial level. In that case, there are usually problems such as too large research area, ignoring the heterogeneity of agricultural production activities in various regions of the province, which leads to the estimation error (ZHANG et al., 2021). The second kind of research usually uses county-level data to measure the agricultural TFP of a specific province or region in China (PENG et al., 2013; CHEN et al., 2020). From the reality of China, the adjacent county-level regions usually belong to the same prefecture-level city in terms of administrative relations, and there is convergence in the formulation of agricultural policies and the use of agricultural production factors (HEARY et al., 2010; LIU et al., 2020a; LIU et al., 2020b; WANG et al., 2021). Suppose the county-level data is used to measure China's agricultural TFP. In that case, the research area is often too narrow. The agricultural production factors tend to be the same, leading to the deviation between the actual measurement results. China is a local administrative level of the "province-city-county-township" four-level system. With the continuous development of urbanization, prefecture-level cities have gradually become critical administrative centers. Using the prefecture-level city data to measure agricultural total factor productivity, the sample size is moderate, and the data is easy to obtain, which can effectively solve the problems of too extensive regional range of provincial data, significant internal differences, lack of county data and too large amount of data.

To sum up, the innovations of this paper can be summarized as follows: (1) from the research perspective, this paper focused on the spatiotemporal differentiation and spatial correlation characteristics of agricultural TFP of prefecture-level cities in China. (2) In terms of research methods, considering the heterogeneity of agricultural production in various regions, this paper used the Metafroniter-Malmquist index to measure agricultural TFP. The model can make a reasonable distinction according to the agricultural development of different prefecture-level cities, divide prefecture-level cities with homogeneity of agricultural development, and calculate the frontier efficiency and common frontier efficiency within the group, respectively. This can effectively avoid the estimation error caused by regional heterogeneity between samples, and the conclusion is closer to the actual situation. In addition, according to the measurement results, this paper further discusses the spatial correlation of agricultural TFP growth in China by using the Moran index. (3) In terms of data selection, this paper innovatively adopts the panel data of agricultural production of 283 prefecture-level cities in China from 2001 to 2018 as the research sample. The sample has an extensive period and a large number, which can provide new data processing ideas for relevant research to provide more scientific theoretical guidance for improving China's agricultural TFP.

MATERIAL AND METHODS

Agricultural TFP index based on non-parametric common frontier

According to OH & LEE (2009) Metafrontier-Malmquist index method, we calculated the agricultural TFP of prefecture-level cities in China. The form of the model is as follows:

Firstly, the group Malmquist productivity index (GMI) is defined as the following function:

$$GMI_t^{t+1}(x^t,y^t,x^{t+1},y^{t+1})=\frac{\vec{D}_G(x^{t+1},y^{t+1})}{\vec{D}_G(x^t,y^t)} \tag{1}$$

Where, $\vec{D}_G(x,y)$ is the direct distance function in groups. We can further decompose the GMI index:

$$\begin{aligned} &GMI_t^{t+1}(x^t,y^t,x^{t+1},y^{t+1})\\ &=\frac{\vec{D}_G^{t+1}(x^{t+1},y^{t+1})}{\vec{D}_G^{t}(x^t,y^t)}\times\left\{\frac{\vec{D}_G(x^{t+1},y^{t+1})}{\vec{D}_G^{t+1}(x^{t+1},y^{t+1})}\times\frac{\vec{D}_G^{t}(x^t,y^t)}{\vec{D}_G(x^t,y^t)}\right\}\\ &=\frac{\vec{D}_G^{t+1}(x^{t+1},y^{t+1})}{\vec{D}_G^{t}(x^t,y^t)}\times\left\{\frac{\vec{D}_G(x^{t+1},y^{t+1})/\vec{D}_G^{t+1}(x^{t+1},y^{t+1})}{\vec{D}_G(x^t,y^t)/\vec{D}_G^{t}(x^t,y^t)}\right\}\\ &=\frac{TE^{t+1}}{TE^t}\times\frac{BPG^{t+1}}{BPG^t}=EC\times BPC \end{aligned} \tag{2}$$

Secondly, the global Malmquist productivity index (MMI) without grouping can be defined as the following function form:

$$MMI_t^{t+1}(x^t,y^t,x^{t+1},y^{t+1})=\frac{\vec{D}_M(x^{t+1},y^{t+1})}{\vec{D}_M(x^t,y^t)} \tag{3}$$

Where, $\vec{D}_M(x,y)$ is the global direction distance function. We can further decompose MMI index:

$$\begin{aligned} &MMI_t^{t+1}(x^t,y^t,x^{t+1},y^{t+1})\\ &=\frac{\vec{D}_G^{t+1}(x^{t+1},y^{t+1})}{\vec{D}_G^{t}(x^t,y^t)}\times\left\{\frac{\vec{D}_M(x^{t+1},y^{t+1})}{\vec{D}_G^{t+1}(x^{t+1},y^{t+1})}\times\frac{\vec{D}_M(x^t,y^t)}{\vec{D}_G^{t}(x^t,y^t)}\right\}\\ &=\frac{\vec{D}_G^{t+1}(x^{t+1},y^{t+1})}{\vec{D}_G^{t}(x^t,y^t)}\times\left\{\frac{\vec{D}_G(x^{t+1},y^{t+1})}{\vec{D}_G^{t+1}(x^{t+1},y^{t+1})}\times\frac{\vec{D}_G^{t}(x^t,y^t)}{\vec{D}_G(x^t,y^t)}\right\}\times\left\{\frac{\vec{D}_M(x^{t+1},y^{t+1})}{\vec{D}_G(x^{t+1},y^{t+1})}\times\frac{\vec{D}_G(x^t,y^t)}{\vec{D}_M(x^t,y^t)}\right\}\\ &=\frac{TE^{t+1}}{TE^t}\times\frac{BPG^{t+1}}{BPG^t}\times\frac{TGR^{t+1}}{TGR^t}=EC\times BPC\times TGC \end{aligned} \tag{4}$$

In formula (1)-(4), *EC* represents the change in technical efficiency from period *t* to *t+1*. *BPG (Best Practice Gap)* represents the gap between the current and intra-group frontier within each group. *BPC (Best Practice Change)* represents the change in *BPG* from period *t* to *t+1*, which is usually used to reflect DMU's technical progress. *BPC>1* indicates that the efficiency of each DMU in the group is getting closer and closer to the intra-group frontier, and the technical level is improved. Conversely, when *BPC<1* indicates that the efficiency of each DMU in the group is getting farther and farther away from the intra-group frontier, and the technical level is not improved. *TGR* is the gap between the frontier of each group and the common frontier, which is the ratio of the technology gap. *TGC* is the change of TGR from period *t* to *t+1*. *TGC>1* means that the distance between the intra-group frontier to the common frontier becomes smaller over time, and vice versa. The relationship between MMI and GMI are shown in figure 1.

Spatial Autocorrelation

The common method of spatial correlation test is the Moran index, which usually includes the global Moran index and local Moran index. The global Moran index is mainly used to judge the spatial agglomeration of the whole sample. The formula for calculating is as follows:

$$Global\ Moran's\ I_{it}=\frac{\sum_{i=1}^{n}\sum_{j=1}^{n}w_{ij}(x_i-\bar{x})(x_j-\bar{x})}{S^2\sum_{i=1}^{n}\sum_{j=1}^{n}w_{ij}} \tag{5}$$

Where S^2 is the sample variance w_{ij} is the spatial weight matrix. The value of global Moran's I is generally between (-1,1). If Moran's I>0, there is a positive correlation in space. If Moran's I<0, there is a negative correlation in space. If Moran's I=0, there is no correlation in space.

The local Moran index is mainly used to judge the spatial agglomeration near an area, and the calculation formula is as follows:

$$Local\ Moran's\ I_{it}=\frac{(x_i-\bar{x})\sum_{j=1}^{n}W_{ij}(x_j-\bar{x})}{\sum_{i=1}^{n}(x_i-\bar{x})^2\Big/n} \tag{6}$$

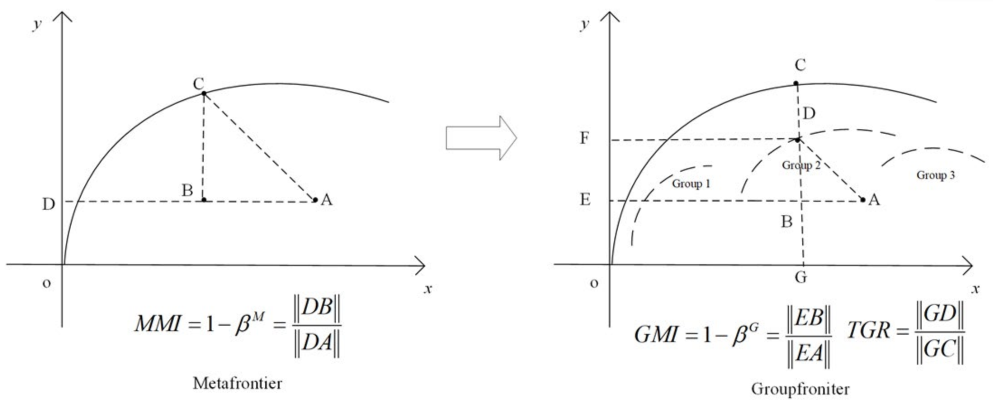


Figure 1 - Metafrontier (MMI), Groupfrontier (GMI) and Technology Gap Ratio (TGR).

Local spatial correlation is usually described by Moran scatter diagram. The horizontal axis represents the current value of the sample variable, and the vertical axis represents the spatial lag term. The four quadrants of the graph divided the spatial correlation between the sample area and its neighboring areas into four relationships: "high-high" (HH), "high-low" (HL), and "low-low" (LL) and "low-high" (LH). Among them, "high-high" (HH) and "low-low" (LL) indicated that there is a significant spatial positive correlation between the research samples, that is, the sample area is a high value (low value), and the surrounding area is also high value (low value); The "high-low" (HL) and "low-high" (LH) indicated that there is a significant negative spatial correlation between the samples, that is, the sample area is a high value (low value), but the surrounding area is a low value (high value).

Data & descriptive statistics

Index Selection

According to the research of LI et al. (2020), LIU et al. (2021), MA et al. (2021), and careful consideration of the availability of sample data, this paper selects the total power of agricultural machinery (10,000 kW), the amount of pure fertilizer application (10,000 tons), rural power consumption (100 million kW), effective irrigation area (hectares), crop sown area (hectares) and the number of employees in the primary industry (10 thousand people) as the input variables. This paper used each city's total agricultural output value (100 million yuan) as the output variable. It is worth noting that the common input of agricultural production factors usually includes pesticides use and plastic film use (LIU et al.,2020c; XU et al.,2019), but these two indicators are seriously missing in the municipal samples, so this paper does not include them in the input indicators for calculation.

Data Sources

In order to fully reflect the changing state and trend of China's agricultural TFP since the 21st century, this paper sets the research time as 2001-2018. All the input and output variables are from *the "China Urban Statistical Yearbook"* and "*China Regional Economic Statistical Yearbook,"* as well as the statistical yearbooks, statistical bulletins, and rural economic yearbooks of provinces, municipalities, and autonomous regions. It should be noted that *the "China Regional Economic Statistical Yearbook"* has not been published since 2014. Hence, the input and output of this paper from 2001 to 2013 are mainly from the *"China Regional Economic Statistics Yearbook."* The relevant data of various cities from 2014 to 2018 are collected from the statistical yearbooks, statistical bulletins, and rural economic yearbooks of various provinces, municipalities, and autonomous regions. The data on the rural employment population comes from the *"China Urban Statistical Yearbook."* Data for a small number of missing values in the sample, we used the linear interpolation method to make the missing values. The data selected only includes mainland China, excluding Hong Kong, Macao, and Taiwan. At the same time, due to the severe lack of relevant data in Shenzhen, Zhongwei, and Lhasa, the administrative regions of Chaohu, Bijie, Tongren, and Sansha change frequently, we eliminated the above-mentioned prefecture-level cities in the process of analysis.

Finally, panel data of 283 prefecture-level cities in 30 provinces, municipalities, and autonomous regions for 18 years are selected for analysis. The specific sources of each variable are shown in table 1. The measurement of agricultural TFP in 283 prefecture-level cities in the sample is based on the Malmquist index method with constant returns to scale, using MaxDEA Pro 6.18.

Study Region

It is a significant problem to divide groups reasonably by using Metafrointer- Malmquist index to measure productivity. The division of groups should ensure that the level of agricultural production technology of each prefecture-level city in the group is the same or similar. In contrast, the level of agricultural production technology among groups should show apparent heterogeneity. According to the *"Plan for Sustainable Agriculture Development in China (2015-2030)"*, and comprehensively considering the factors such as the level of economic development and the basis of agricultural development in various parts of China. Divide China into three groups: priority development area, moderate development area, and conservation and development area. The number of provinces and prefecture-level cities in the specific study area is shown in table 2.

RESULT & DISCUSSION

This paper uses the Metafrointer-Malmquist index to measure the agricultural TFP index of 283 prefecture level cities in China from 2001 to 2018. On this basis, the results are displayed and discussed from the national level, regional level, and prefecture level.

Results and discussions of agricultural TFP at the national level

Figure 2 shows China's agricultural TFP and its decomposition from 2001 to 2018 at the national level. Firstly, the MMI index of China's agricultural TFP is 1.664, which indicates that the average annual growth rate of China's agricultural TFP is 6.64%. Secondly, from the source of growth, the annual growth of technology efficiency (EC) and technological progress (BPC) are 0.95% and 6.63%, indicating the growth rate of agricultural TFP in China has been driven by the progress of agricultural technology level. It means there is a typical "single-wheel-drive" phenomenon in promoting the growth rate of agricultural TFP in China, and the growth structure needs to be further improved. If only relying on technological progress to promote the growth of agricultural TFP will produce high costs, resulting in the widening gap between regions. Thirdly, the average annual growth rate of the technology gap improvement index (TGC) is -0.62%, which indicates that the gap between the TFP growth of various regions and the overall TFP level of the whole country is narrowing. However, there is still a particular room for improvement.

In addition, the highest growth point of agricultural TFP occurred in 2007-2008, with an increase of 15.8%, a high growth rate. The lowest point occurred in 2002-2003, with an increase of only 1.2%. Although, the growth rate is not high, it is still in a state of positive growth. The time change of the MMI index shows the "inverted U-shaped" feature of rising first and falling second, and the growth inflection point appears around 2010. After 2010, China entered the "Twelfth-Five-Year Plan" development stage, and economic growth has gradually changed from high-speed growth to high-quality development. The implementation of economic structural reform has led to a structural slowdown in economic development, which has a particular impact on the growth of TFP and slowed down its growth rate. In addition, with the rapid development of China's tertiary industry in recent years, some factors of production flow from the primary industry to the tertiary industry, and the

Table 1 - Statistical description of variables.

Index	Unit	Obs.	Mean	Std. Dev	Max	Min
the total power of agricultural machinery	10,000 kw	5094	277.912	270.205	2118.597	0.600
the amount of pure fertilizer application,	10,000 tons	5094	17.643	15.592	104.743	0.040
rural power consumption	100 million kw	5094	22.104	57.642	8.797	1053.4
effective irrigation area	hectares	5094	180.621	149.684	1.82	875.6
crop sown area	hectares	5094	506.935	406.472	3575.8	3.3
the employed agriculture	10 thousand people	5094	1.101	3.373	95.58	0.0014
the total agricultural output value	100 million yuan	5094	214.244	191.052	2052.4	1.0115

Table 2 - Division of Group Area.

Type	Area	Province (Number of city)
Priority Development Area	Northeast China	Liaoning (14), Jilin (8), Heilongjiang (12)
	North China	Beijing (1), Tianjin (1), Hebei (11), Henan (17), Shandong (17)
	The middle and lower reaches of the Yangtze River	Shanghai (1), Jiangsu (13), Zhejiang (11), Anhui (16), Jiangxi (11), Hubei (12), Hunan (13)
	South China	Guangdong (20), Fujian (9), Hainan (2)
Moderate Development Area	Northwest China	Xinjiang (2), Ningxia (4), Shanxi (11), Shaanxi (10), Gansu (12), Inner Mongolia (9)
	Southwest China	Guangxi (14), Guizhou (4), Chongqing (1), Sichuan (18), Yunnan (8)
Conservation and development area	Qinghai and Tibet Region	Qinghai (1)， Tibet (0)

adjustment of industrial structure also leads to the slowdown of agricultural TFP growth.

From the result of agricultural TFP at the national level, we can find that: the growth source of China's agricultural TFP is mainly driven by the advancement of agricultural technology. The slow growth of agricultural technical efficiency is one of the critical problems in agricultural production. The "two-wheel-drive" growth mode should become the primary mode of China's agricultural economic growth in the future. Therefore, it is necessary to strengthen the promotion and high-efficient utilization of agricultural production technology in the future, improve the transformation and extension system of agricultural scientific and technological achievements, and improve the use efficiency of agricultural production factors.

Results and discussions of agricultural TFP at the regional level

Figure 3 shows the average distribution of agricultural TFP in China from 2001 to 2018. The agricultural TFP has significant regional unbalanced growth characteristics during the sample period. Agricultural TFP of the priority development area, moderate development area, and conservation and development area increased by 6.44%, 7.01%, and 9.89%, respectively. Among them, the average agricultural TFP of North China, Northeast China, the middle and lower reaches of the Yangtze River, and South China in the priority development area are 8.35%, 5.15%, 6.78%, and 4.16%, respectively. The average agricultural TFP in the northwest and southwest of the moderately developed area was 8.22% and 5.73%, respectively. The average

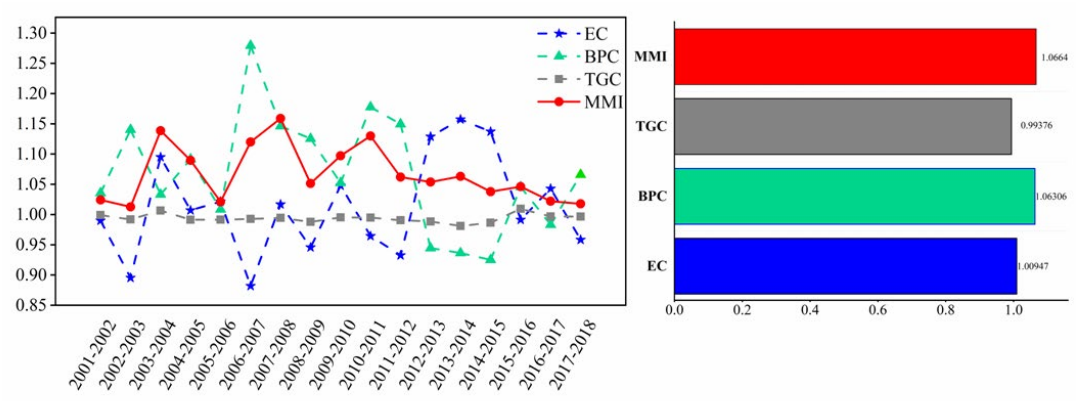
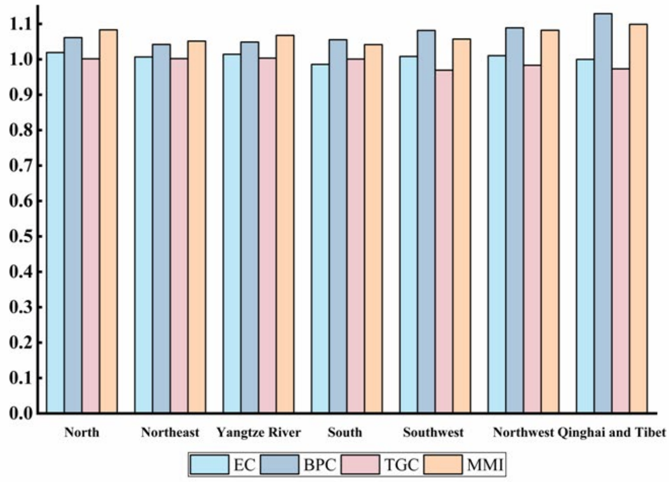
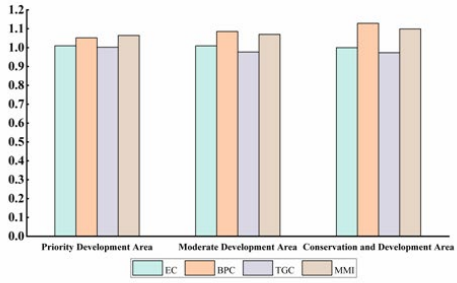


Figure 2 - Agricultural total factor productivity and its decomposition at national level from 2001 to 2018.





Regional agricultural TFP

Area	EC	BPC	TGC	MMI
North	1.01923	1.0615	1.00152	1.08356
Northeast	1.00684	1.04219	1.00213	1.05155
Yangtze River	1.01448	1.04884	1.00359	1.06785
South	0.98597	1.0556	1.00086	1.04169
Priority Mean	1.00955	1.05188	1.00236	1.06444
Southwest	1.00825	1.08164	0.96958	1.05739
Northwest	1.01049	1.08903	0.98345	1.08225
Moderate Mean	1.00941	1.08545	0.97672	1.07015
Qinghai and Tibet	1	1.12902	0.97334	1.09893
Conservation Mean	1	1.12902	0.97334	1.09893

Figure 3 - Spatial distribution characteristics of agricultural total factor productivity in different regions of China from 2001 to 2018.

agricultural TFP of Qinghai in the protection and Development area reached 9.89%. Next, we will discuss this growth law and the factors affecting agricultural TFP in different regions.

First, the priority development area is the main production area of bulk agricultural products in China. It has good agricultural production conditions, great potential, advanced agricultural production technology, and a high agricultural marketization. However, in the development process, there are also problems of excessive use of agricultural inputs and a low degree of resource recycling. The agricultural policy in this area requires that we prioritize production, give consideration to ecology and combine planting and breeding. On the premise of ensuring the steady improvement of the total production capacity of major agricultural products such as grain, the steady improvement of agricultural TFP will be realized. Thus, the agricultural TFP in the priority development area is equal to that in the common frontier. The priority development areas include Northeast China, North China, the middle and lower reaches of the Yangtze River, and South China. From the calculation results, North China > the middle and lower reaches of the Yangtze River > Northeast > South China. Firstly, there are significant differences in the natural conditions of agricultural production in various regions. North China is located in the north of China. The terrain of this area is mainly plain, with high soil fertility and a mild and humid climate. The middle and lower reaches of the Yangtze River and South China are mainly hilly and mountainous. The climate in Northeast China is cold, which makes the agricultural development greatly affected by natural factors. Therefore, North China has inherent natural advantages in agricultural production compared with other regions. Secondly, there are significant differences in regional economic development. North China has a long history of agricultural production, developed agricultural industry, and high agricultural production technology. The service industry in the middle and lower reaches of the Yangtze River and South China is relatively developed. The tertiary industry dominates the industrial structure, and many production factors flow to the tertiary industry. Therefore, the growth of agricultural TFP is relatively slow.

Second, the agricultural production characteristics of moderate development area are distinctive. However, the ecology in this area is fragile. The allocation of water and soil is misplaced, the water shortage of resources and engineering is severe, the carrying capacity of resources and environment is limited, and the agricultural infrastructure is relatively weak. In terms of agricultural policies, the moderate development area requires that equal attention be paid to protection and development, based on resources and environmental endowment, give full play to its advantages, moderately tap its potential and improve the utilization rate of resources. Therefore, once the moderate development area seizes the development opportunity, it will accelerate the improvement of agricultural production mode and promote the promotion of agricultural TFP. This is bound to have a “catch-up effect.” This also explains the high progress of agricultural technology in moderately developed areas. The moderately developed areas include the northwest and southwest regions. From the calculation results, the northwest region > the southwest region. Although, the growth of agricultural TFP in Northwest China is relatively fast, it is mainly driven by technological progress, and the growth quality is not high. The harsh natural environment makes the northwest continuously promote agricultural growth by improving agricultural production technology in agricultural development, thus ignoring the efficiency of agricultural production.

Third, the protection and development is the birthplace of China’s major rivers and a significant ecological security barrier. The plateau is rich in agricultural resources, but the ecology is very fragile. Formulating agricultural policies in this region requires priority to protection, limiting development, and moderately developing ecological and characteristic industries. However, the agricultural TFP in the protected development area has the fastest growth rate from the calculation results. This is a critical issue. Like the moderate development area, the agricultural development level of the protection and development area is relatively backward. With the spread of advanced agricultural technology in recent years, the protection and development area has promoted a significant increase in agricultural total factor productivity through the progress of agricultural technology. Therefore, we should pay attention to the combination of agricultural development, ecological environment, and resource protection in the future.

Figure 4 shows the time evolution trend of agricultural TFP in the three regions. It can be reported that the time evolution trend of agricultural TFP in the three regions is consistent with that in the common frontier. The TFP of priority and moderate development areas fluctuate more minor than the shared frontier. In contrast, the agricultural TFP of protected development areas fluctuates more than the common frontier. In addition, the growth trend of the three regions is also in line with the “inverted U-shaped” law of rising first and falling second.

Results and discussions of agricultural TFP at the prefecture-level cities level

According to the difference of agricultural TFP and spatial geographical location, we divide 283 prefecture level cities into four different types of growth modes, as shown in figure 5 below.

The first mode is the high-speed growth mode. The characteristic of this model is that the agricultural total factor productivity of prefecture-level cities is much higher than the national average level under the common boundary. It mainly includes 39 prefecture-level cities. The priority development area includes 25 prefecture-level cities, such as Nanjing, Wuxi, Suzhou, Guangzhou, and Zhuhai. The moderate development area includes 14 prefecture-level cities, such as Xi’an in Shaanxi. From the perspective of growth sources, the growth rate of agricultural TFP in some prefecture-level cities is driven by technological progress and technical efficiency. However, there are still many prefecture-level cities relying on a single factor to drive the growth rate of agricultural TFP.

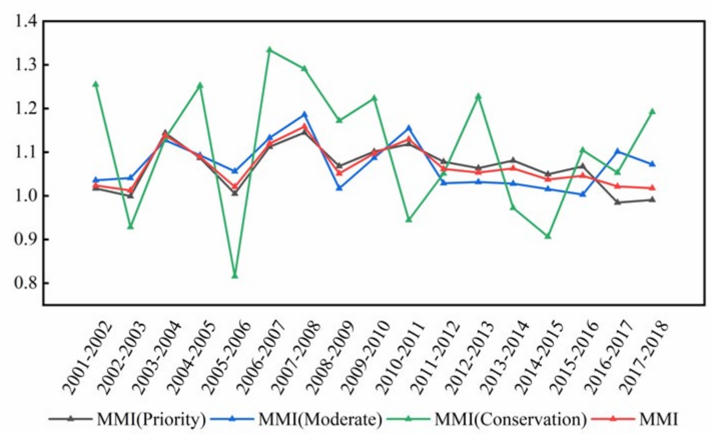


Figure 4 - Time distribution characteristics of regional agricultural Metafrontier Malmquist Index (MMI) from 2001 to 2018.

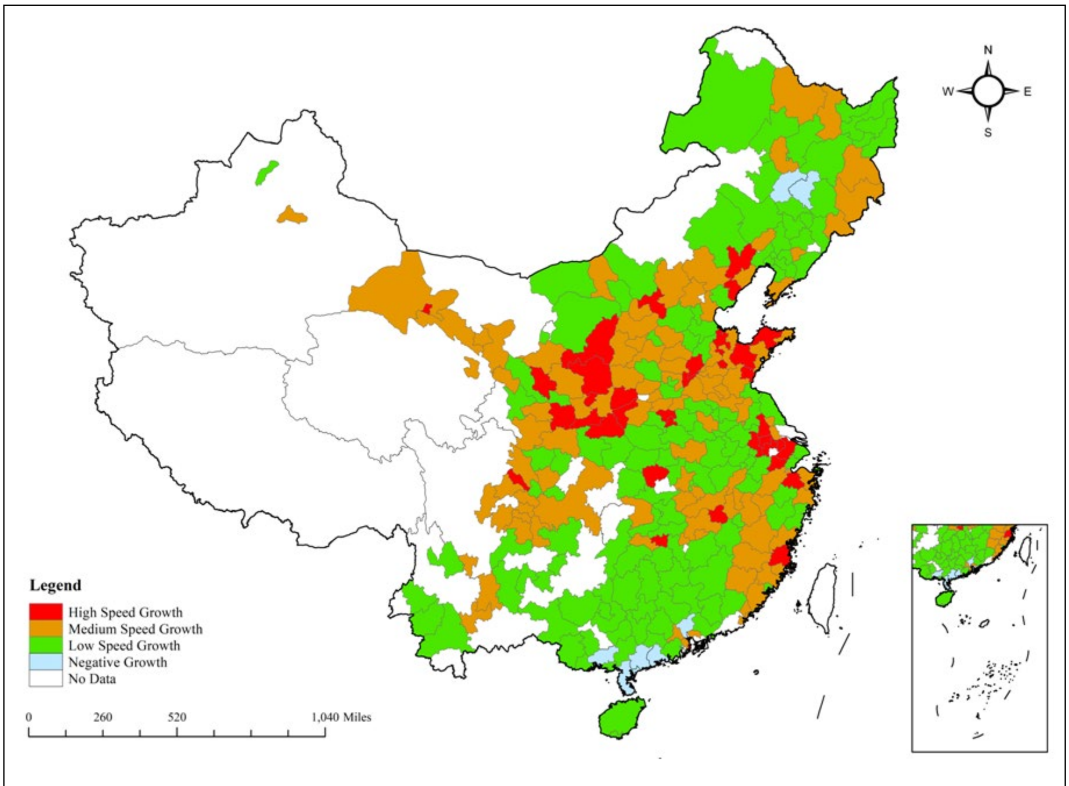


Figure 5 - Mean value distribution of agricultural total factor productivity with different growth rates.

The second model is the medium-growth model. The characteristics of this model are: Agricultural TFP is slightly higher than the national average level under the common frontier. Most of the growth sources of these prefecture-level cities are driven by single technological progress. It mainly includes 102 prefecture-level cities. The priority development zone includes 65 prefecture-level cities, such as Beijing, Tianjin, Shijiazhuang, Hebei, Hangzhou, Zhejiang, Wuhan, Hubei, and other prefecture-level cities. The moderate development zone includes 36 prefecture-level cities, such as Chongqing, Taiyuan, Sichuan Chengdu, Kunming, Yunnan, Lanzhou, Gansu, and other prefecture-level cities. The protection and development zone includes a prefecture-level city, Xining, Qinghai. Among these prefecture-level cities, the BPC of most prefecture-level cities is higher than the national average, which shows that the growth rate of agricultural TFP in these prefecture-level cities mainly depends on the “single wheel drive” of technological progress. The effect of technical efficiency in improving the growth rate of agricultural TFP in prefecture-level cities is not apparent.

The third is the slow-growth model. The characteristics of this model are: the average annual growth rate of agricultural TFP is positive but lower than the national average level under the common frontier. It mainly includes 136 prefecture-level cities. The priority development areas include 94 prefecture-level cities, such as Shanghai, Liaoning Shenyang, Heilongjiang Harbin, Anhui Hefei, and Hunan Changsha. The moderately developed area includes 42 prefecture-level cities, such as Nanning and Fangchenggang in Guangxi, Guiyang in Guizhou, Yinchuan in Gansu, and Karamay in Xinjiang. These prefecture-level cities’ EC, BPC, and MMI are slightly lower than the national average level. However, from the perspective of growth sources, there is still a “single wheel” driving TFP improvement of technological progress, and the speed of technical efficiency improvement is slow.

The fourth is the negative-growth model. In these groups, the agricultural TFP index is less than 1, indicating negative growth and slow agricultural growth. It mainly includes six prefecture-level cities. There are five prefecture-level cities with negative growth in the priority development area, including

Jilin Changchun, Guangzhou, and Guangdong. Qinzhou, Guangxi, is one prefecture-level city with negative growth in moderately developed areas. These prefecture-level cities are subject to improved agricultural technology levels, the loss of agricultural production technology efficiency, and the change in the industrial economic structure of prefecture-level cities, resulting in negative growth in these areas.

Results and discussions of spatial correlation

It can be seen from figure 5 that there are significant differences in the spatial distribution of agricultural TFP in 283 prefecture-level cities. Further, we can also find that different groups of agricultural TFP show a significant phenomenon of spatial agglomeration in space. In other words, the agricultural TFP levels of local-level cities and their neighboring prefecture-level cities are similar to each other to a great extent. Therefore, to further reveal the spatial characteristics of agricultural TFP in various cities, this paper uses the Moran index method in spatial statistics to analyze the spatial correlation of agricultural TFP in various cities. The spatial distance matrix constructed in this paper is the geographical distance matrix, the reciprocal of the square of the spatial distance of each prefecture-level city.

We calculated the global Moran index of agricultural TFP in each prefecture-level city. The calculation results are shown in figure 6 below. From the global Moran index calculation results, we can find that there is a positive spatial correlation of agricultural TFP in all cities in China during the sample period, and it is significant at the significance level of 1% in most years. From the changing trend, we can see that the spatial correlation of local cities increases year by year with time.

Figure 7 shows the local Moran scatter diagram of agricultural TFP in 283 prefecture-level cities in China. We can find that most prefecture-level cities are distributed in the first quadrant and the third quadrant. It shows that the agricultural TFP of each prefecture-level city presents "high-high" agglomeration and "low-low" agglomeration in space. The result is consistent with the research conclusion of JIN et al. (2019). It shows a significant peer effect and a spatial spillover effect in agricultural TFP of prefecture-level cities. From the perspective of reasons, the cross-regional flow of agricultural production factors is an important reason for the existence of spatial correlation. According to the technology diffusion model theory of Suzuki, it can be known that interregional agricultural development will effectively spread among regions through knowledge and technology to narrow the gap in agricultural production efficiency between regions. Therefore, the growth rate of agricultural TFP in prefecture-level cities has a certain degree of spatial correlation effect. The growth level of agricultural

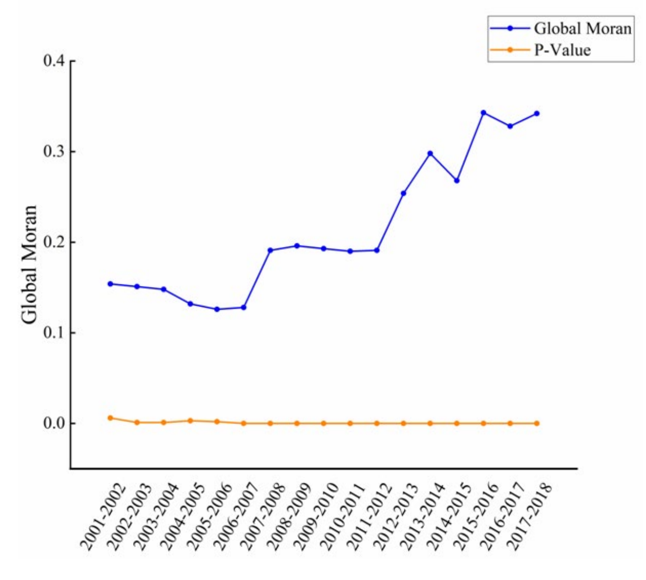


Figure 6 - Global Moran index evolution of agricultural total factor productivity in Chinese cities from 2001 to 2018.

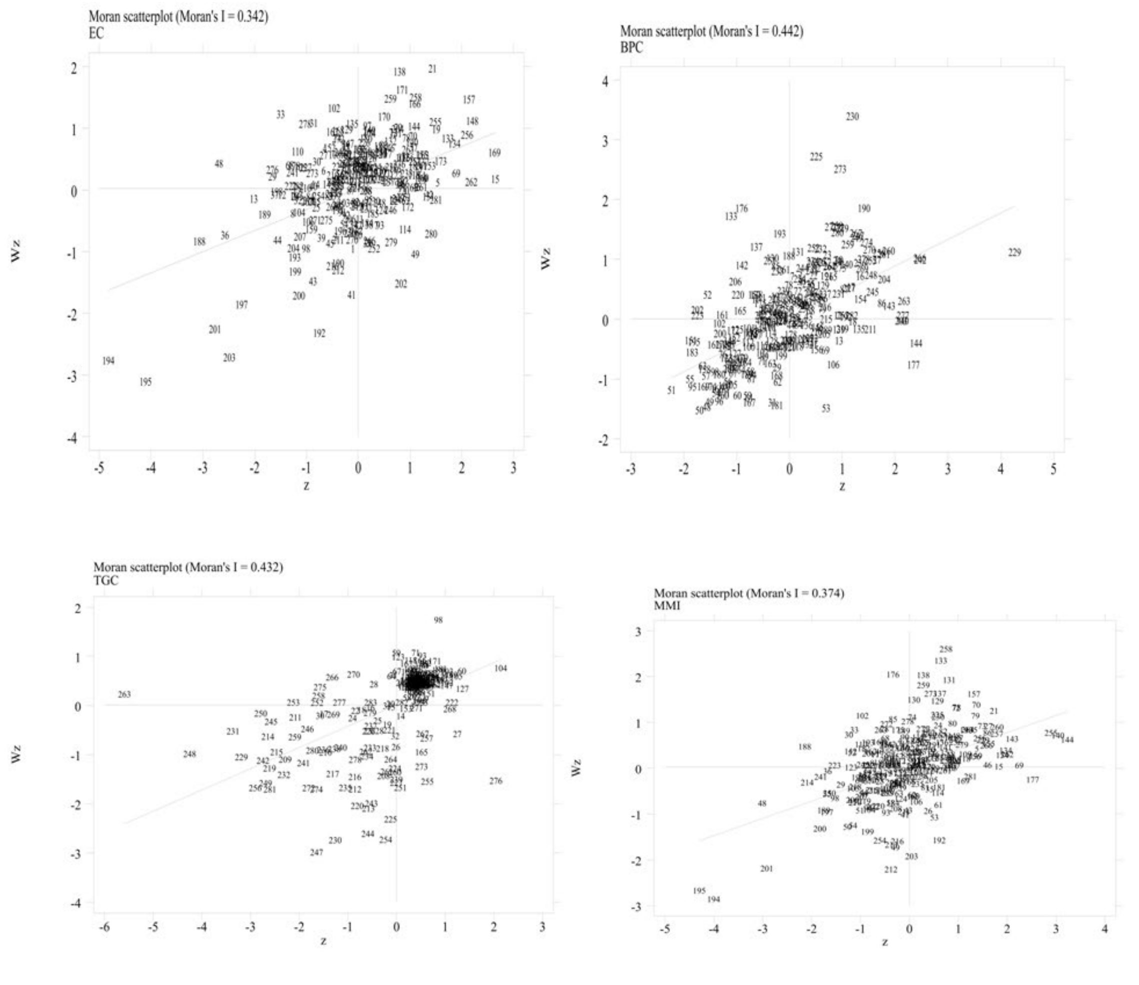


Figure 7 - Local Moran scatter of agricultural total factor productivity in 283 prefecture level cities of China.

TFP in a prefecture-level city will impact the growth level of agricultural TFP in surrounding prefecture-level cities.

From the calculation results of spatial correlation, we should pay full attention to the spatial correlation of agricultural TFP. Strengthen the interaction of agricultural production in neighboring prefecture-level cities, promote the rational cross-regional flow of agricultural technology, talents, capital, and other production factors, and strengthen the information flow and technology sharing of agricultural production among prefecture level cities. At the same time, prefecture-level cities with a high growth level of agricultural TFP should play their radiation driving role, promote the standard promotion and coordinated development of agricultural TFP, and improve the growth quality of agricultural TFP.

CONCLUSION

This paper selects the panel data of 283 prefecture-level cities in China from 2001 to 2018, calculates the agricultural TFP of prefecture-level cities using the Metafrontier-Malmquist index, and discusses the spatiotemporal differentiation of agricultural TFP. According to the calculation results, we used the Moran index to discuss the spatial correlation of agricultural TFP. The main conclusions included the following: (1) From 2001 to 2018, China's agricultural TFP increased by 6.64%. The growth of agricultural TFP mainly depends on the progress of agricultural technology, and the contribution of agricultural production efficiency is minor. (2) China's agricultural TFP growth has significant characteristics of regional imbalance.

(3) The agricultural TFP growth modes of most prefecture-level cities belong to medium and slow speed, and the prefecture-level cities with “single-wheel-drive” growth account for the majority. (4) The agricultural TFP of prefecture-level cities in China shows a significant spatial correlation in space, and shows a significant phenomenon of “high-high” or “low-low” agglomeration in space.

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DECLARATION OF CONFLICT OF INTEREST

The authors declare no conflict of interest for this article. The founding sponsors had no role in the design of the study, in the collection, analyses, or interpretation of data, in the writing of the manuscript, and in the decision to publish the results.

AUTHORS’ CONTRIBUTIONS

All authors contributed equally for the conception and writing of the manuscript. All authors critically revised the manuscript and approved of the final version.

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