



# Article Sustainable Agricultural Total Factor Productivity and Its Spatial Relationship with Urbanization in China

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**Abstract:** The growth of agricultural total factor productivity (TFP) is seen as a driving force for the sustainable development of agriculture. Meanwhile, the promotion of urbanization in China has exerted a profound impact on agricultural production. This paper calculates the agricultural TFP and analyzes the effect of urbanization. Firstly, the DEA-Malmquist method is used to calculate the dynamic change in agricultural TFP in China from 2004 to 2016. Secondly, the spatial spillover effect of urbanization on agricultural TFP is investigated by the spatial Durbin model. We found that: the average annual growth rate of agricultural TFP in China is 4.8% from 2004 to 2016; and the spillover effect of urbanization on agricultural TFP shows a U-shaped relationship, which means that urbanization has exerted a negative effect first and then a positive effect on agricultural TFP. Finally, the paper puts forward policy suggestions from the perspective of sustainable coordination of urbanization and agricultural production.

Keywords: agricultural total factor productivity; spatial durbin model; urbanization; U-shaped curve



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## 1. Introduction

China has always been the major grain producer and consumer in the world. Ensuring the steady growth of agricultural output is important for the nutrition and health of Chinese citizens. In order to ensure the stable development of agricultural production, the Chinese Government issued the NO.1 Central Documents related to agriculture from 2004 and China's grain production has increased for 12 consecutive years. The continuous growth of agricultural output in China can be attributed to two reasons: the increase in agricultural input factors such as labor force, cultivated land, machinery, pesticide and fertilizer; and the sustainable growth of agricultural total factor productivity (TFP) [1,2]. It is generally believed that the development of China's agricultural production has been driven by high input. Therefore, the growth of agricultural TFP is seen as a better pathway for sustainable development.

The calculation and correction of TFP has always been a topic if interest in academic studies [3–6]. Robert Solow was the first to measure TFP [7]. He proposed the slow residual method to reflect the contribution of technological progress after eliminating the contribution of various input factors. Furthermore, a new production function with controlling unobserved shocks was proposed to solve simultaneity problems [8,9]. In addition, DEA as a nonparametric approach is used to measure efficiency and productivity of decision-making units [10,11]. Meanwhile, SFA as a parametric approach with specific function setting is generally employed to measure technology efficiency based on panel data [12,13].

Agricultural TFP is affected by various factors [14–17]. Gutierrez found that geographical location, international and domestic R&D investment are important factors affecting agricultural TFP [18]. From the perspective of convergence and divergence of agricultural TFP, Paudel et al. found that there was no convergence trend in agricultural TFP among states in the United States, and inter-state differences in agricultural TFP were affected by

the quality of human capital [19]. By measuring the substitution elasticity of agricultural input factors, Gong found that agricultural technological progress and continuous factor input alternately promoted the growth of agricultural output in China [20].

Urbanization is also considered as one of the important factors influencing agricultural TFP, because urban-rural factor allocation market and agricultural production technology are profoundly affected [21,22]. Some scholars have discussed that the urbanization process has imposed a fundamental impact on China's agricultural production [23–25]. Zhao found that the short-term negative effect of urbanization on the technical efficiency of grain production is smaller than the long-term positive effect, and the effects vary among different functional areas of grain in China [26]. Wu et al. pointed out that population urbanization and employment urbanization contribute to promoting the growth of agricultural TFP in China by estimating the panel fixed effect model. Latest research results of Liu et al. show that human capital, level of urbanization, and development flow to agriculture promotes agricultural TFP growth in south and southeast Asian countries [27]. However, Cheng drew the opposite conclusion that population urbanization and employment urbanization have negative effects on the improvement of agricultural carbon productivity [28,29]. In addition, Cai et al. found that the coupling degree between China's new urbanization and the agro-ecological environment is in the antagonistic stage, so there is still great room for improvement [30].

China comprehensively promotes the process of urbanization. According to the China Statistical Yearbook (2020), China's permanent urban population reached 848.43 million and the urbanization rate reached 60.60%. In order to ensure the sustainable growth of agricultural TFP, it is necessary to analyze the mechanism of urbanization on agricultural TFP. On the one hand, urbanization can change the allocation of resources between urban and rural areas. Cities can provide the countryside with machinery, seeds, and advanced technology to improve agricultural total factor productivity continuously. On the other hand, urbanization also brings a series of problems to agriculture, such as a lot of labor migration from rural areas to urban areas, the occupation of farmland by urban construction, and the ecological pollution caused by urbanization and industrialization [31], which may negatively inhibit the sustainable development of agricultural TFP in China. Therefore, urbanization in China may have various effects on agricultural production, which has been explored a lot [32].

#### 2. Theoretical Analysis

Urbanization may have both positive and negative effects on agricultural production. From the perspective of labor migration, on the one hand, with the migration of rural labor force to non-agricultural industries, the marginal productivity of rural labor will be significantly improved, contributing to the increase in labor productivity, thus improving the income level of farmers to a certain extent [33,34]; on the other hand, due to the restriction of the Hukou-household registration system in China, the young and middle-aged rural labor force pursue better job opportunities in the cities [35], which results in more and more women, children and the elderly left in the countryside, so the quality of human capital in rural areas gradually becomes worse [36]. Additionally, the development of urbanization promotes the large-scale intensive use of rural land so as to improve land production efficiency [37]; alternatively, urbanization will also lead to the occupation of large amounts of arable land, especially in eastern and central regions of China [38].

The relationship of urbanization and agriculture has aroused the attention of many scholars. From the perspective of urban-rural income gap and agricultural growth, there may be a U-shaped relationship, which diverts rural resource out of agricultural sector to urban sector [39,40]. As for urbanization and agricultural productivity, increasing population density increases agricultural productivity at the rural-urban fringe, while increasing urban fragmentation may have a detrimental effect on agricultural productivity at low levels of fragmentation [41].

It is also worth noting that urbanization and agricultural production have spatial attributes. The urbanization development of the surrounding areas is likely to have a certain impact on that of local regions. The exchange of population, land, investment and technology in adjacent regions will interact and influence each other [42]. Similarly, agricultural TFP may have spatial convergence [43]. This phenomenon is more easily observed when two adjacent regions have similar geographical characteristics. Natural conditions, agricultural production mode, economic characteristics, and agricultural technology diffusion of adjacent regions have a certain degree of correlation, which can be understood as geographical, economic, and institutional correlation [44]. Therefore, the impact of urbanization on agricultural TFP may have a strong spatial spillover effect.

In the view of the complex relationship between urbanization and agricultural TFP, both the direction and the degree of the impact may vary with spatial and temporal change. Therefore, the relationship between urbanization and agricultural TFP may not be limited to a linear one. In addition, these influences of urbanization on agricultural TFP not only take place in one region but are also related to neighborhoods from the spatial perspective. Therefore, this paper argues that urbanization has both a "siphon effect" and "trickle effect" on agricultural TFP by using spatial econometric model to identify spatial spillover effect [45–48].

However, it seems that there is little literature about the U-shaped relationship verification between urbanization and agricultural TFP in China from the spatial perspective. According to the above theoretical analysis, this paper aims at filling the gap of identifying the impact of urbanization on agricultural TFP from the perspective of space. Further, this paper puts forward the hypothesis that the impact of urbanization on agricultural TFP may present a U-shaped curve relationship. In this paper, urbanization which affects agricultural TFP is defined as a core explanatory variable. The U-shaped curve relationship between urbanization and agricultural TFP may exist. In addition, the spatial direct effect, indirect effect, and total effect of urbanization will be analyzed.

In the first stage of urbanization, before the arrival of the "inflection point", the urbanization development level is relatively low, and the speed is fast. The rapid expansion of cities requires lots of high-quality labor, farmland and investment from rural areas. Therefore, the impact of urbanization on agricultural TFP growth may be negative. In the second stage of urbanization, after the arrival of the "inflection point", the development level of urbanization in this stage is relatively high, and more attention will be paid to the development quality of urbanization rather than the development speed of urbanization. A large amount of investment, advanced technology and high-quality human capital from cities will be invested in rural areas. Therefore, at this stage, urbanization will improve the resource allocation efficiency and agricultural TFP.

#### 3. Materials and Methods

This section is divided by subheadings, which provides a concise and precise description of data source, variable summary, DEA–Malmquist model, and spatial Durbin model.

#### 3.1. DEA–Malmquist Index

The DEA–Malmquist index can be employed to measure agricultural TFP. Charnes et al. were the first to construct the data envelope analysis method (DEA) [49]. The method is a kind of nonparametric estimation, so there is no need to set up the specific input–output function. The effective production frontier can be estimated by establishing an optimized non-parametric estimation model with input and output data. Then, efficiency difference and dynamic trends of different decision-making-units (DMU) can be compared. In this study, based on the premise of constant return to scale (CRS), output, the oriented DEA– Malmquist index method is adopted to measure agricultural TFP in China. Agricultural TFP can be decomposed into technical efficiency change and technological change within two production periods [50]. Therefore, the changing state of production front can be observed and analyzed. Firstly, the scope of input factor and output factor is determined. The set of production possibilities for the entire production cycle is defined as St, which can be interpreted as the set of possibilities that input x can produce y in period t. The production activity in S period is defined as  $(x_s, y_s)$ , and the output distance function can be obtained as:

$$D(x, y) = [\sup\{\theta : (x, \theta y) \in S\}]^{-1}$$
(1)

Then, the Malmquist productivity index from t period to t + 1 period can be obtained on the basis of the direction distance function [51]. The weighted average of the Malmquist productivity index can be used to obtain total factor productivity (TFP):

$$M_0^{t+1} = D_0^{t+1} \left( X^{t+1}, Y^{t+1} \right) / D_0^t \left( X^t, Y^t \right)$$
(2)

Furthermore, total factor productivity can be decomposed into the change in technical efficiency ( $\triangle$ TE), the change in technological progress ( $\triangle$ T) and the change in scale efficiency ( $\triangle$ S):

$$TFP = \triangle TE \cdot \triangle T \cdot \triangle S.$$
(3)

The added value of the primary industry (AVPI) is selected as the output indicator of agricultural TFP. AVPI is a more accurate representation of changes in agricultural output. Due to data availability, the research period is restricted to 2004–2016. In addition, AVPI is deflated with 2004 as the base period to reduce the interference of inflation. The unit is AVPI is 100 million CNY.

Notably, the data of Tables 1 and 2 is stated to rely fully on secondary data, including: the China Statistical Yearbook, the China Rural Statistical Yearbook, the China Agriculture Yearbook, the China Agricultural Machinery Industry Yearbook, and so on. The number of primary industry employment is used as a measure of labor input indicator, which can reflect the actual utilization of agricultural labor force in different periods. The total area sown is used as an indicator to measure land input. Total horsepower of agricultural machinery is used as the index to measure the input of machinery. Fertilizer input is measured by the amount of nitrogen and phosphate fertilizer actually applied to agricultural production.

## **Table 1.** Description of the variables in DEA calculation.

Variable	Unit	Definition Measuring Method	Data Source
Output	100 million CNY	The added value of the primary industry (AVPI)	China Statistical Yearbook
Labor input	10 thousand people	The number of employees in the primary industry	China Statistical Yearbook
Land input	10 thousand hectare	The total areas of crops sown	China Rural Statistical Yearbook
Machinery input	10 thousand kilowatt	The total horse power of agricultural machinery	China Agricultural Machinery Industry Yearbook
Fertilizer input	10 thousand ton	The amount of nitrogen and phosphate fertilizer actually applied to agricultural production	China Agriculture Yearbook

Table 2. Moran index of the cumulative agricultural TFP in China from 2004 to 2016.

Year	Moran's I	Z-Statistic	<i>p</i> -Value	
2005	0.255	2.644	0.008	
2006	0.255	2.644	0.008	
2007	0.534	4.85	0.000	
2008	0.544	4.997	0.000	
2009	0.477	4.363	0.000	
2010	0.549	4.93	0.000	
2011	0.554	5.043	0.000	

Year	Moran's I	<b>Z-Statistic</b>	<i>p</i> -Value	
2012	0.572	5.138	0.000	
2013	0.598	5.314	0.000	
2014	0.555	4.945	0.000	
2015	0.588	5.237	0.000	
2016	0.564	5.032	0.000	

Table 2. Cont.

## 3.2. Spatial Model Specification

## 3.2.1. Spatial Correlation Test

Before employing the spatial econometric model, it is necessary to test whether the variables to be studied have spatial correlations. At present, Moran's index is the main-stream test method for spatial correlation [52]. The advantage of Moran's index test is that the test results are stable and not easily affected by the data's distribution type. The range of Moran's index is from -1 to 1. When Moran's index is greater than 0, the tested variables have spatial positive correlation. When Moran's index is less than 0, the tested variables have spatial negative correlation. When Moran's index is equal to 0, there is no spatial correlation.

It can be seen from Table 2 that, from 2004 to 2016, the global Moran's index of the cumulative growth rate of agricultural TFP in China is always positive and remains significant at the level of 1%. This test shows that the cumulative growth rate of agricultural TFP in China has a high positive spatial correlation, and the correlation is increasing year by year. From Table 3, the global Moran's index of Urban also passed the test at the significance level of 1%, with *p* values less than 0.01 and Moran's index positive. This indicates that the spatial spillover effect of urbanization in China is positive and remains stable. Based on the results of the Moran's index text, this study can establish a spatial Durbin model by using the 0–1 spatial weight matrix among provinces to analyze the spatial spillover effect of urbanization on agricultural TFP in China.

Year	Moran's I	<b>Z-Statistic</b>	<i>p</i> -Value
2004	0.393	3.565	0.000
2005	0.376	3.554	0.000
2006	0.376	3.554	0.000
2007	0.387	3.641	0.000
2008	0.396	3.717	0.000
2009	0.408	3.824	0.000
2010	0.403	3.76	0.000
2011	0.394	3.686	0.000
2012	0.387	3.624	0.000
2013	0.391	3.656	0.000
2014	0.391	3.657	0.000
2015	0.406	3.779	0.000
2016	0.414	3.858	0.000

Table 3. Moran's index of China's urbanization rate from 2004 to 2016.

#### 3.2.2. Construction of Spatial Regression Model

First, a Hausman test is necessary to determine whether to use the fixed effect model or the random effect model [53]. The result of the Hausman test is (31.18, 0.0002). The Hausman test value is higher than 0 and stays significant at the 1% level. Therefore, the null hypothesis of the random effect model can be rejected, and the spatial Durbin model with the fixed effect is a good choice for estimation. In order to minimize the interference of the endogeneity problem and ensure the accuracy of the estimation results, the spatial Durbin model with bidirectional fixed effect will be used. Secondly, the main spatial model includes the spatial lag model (SLM), spatial error model (SEM), and spatial Durbin model (SDM) [54]. Three models differ significantly in the model specification and interpretation of spatial effects [55]. The spatial Durbin model mainly focuses on the exophytic interaction effect (WX) between the explanatory variable X and the explained variable Y. SDM can better estimate the spatial spillover effect of urbanization on agricultural TFP. Therefore, SDM is selected for quantitative analysis, and the basic equation of the spatial Durbin model is as follows:

$$Y = \rho WY + X\beta + WX\theta + \varepsilon, \ \varepsilon \sim N(0, \delta^2)$$
(4)

where Y is the explained variable; W is the pre-set spatial weight matrix;  $\rho$  is the spatial autoregressive coefficient of the explained variable;  $\beta$  is the parameter to be estimated of the explanatory variable;  $\theta$  is the coefficient of exogenous interaction effect;  $\varepsilon$  is the error term, and it is set to follow the normal distribution with mean value of 0 and variance of  $\delta^2$ . When  $\theta = 0$ , it can be converted into spatial lag model (SLM). When  $\theta = -\rho\beta$ , this is converted to spatial error model (SEM). According to the research needs, the specific regression model can be set as follows:

 $\ln TFP_{it} = W \ln TFP_{it} + \beta_1 Urban_{it} + \beta_2 Urban_{it}^2 + \beta_3 \ln Res_{it} + \beta_4 \ln Market_{it} + \beta_5 \ln Labor_{it} + \beta_6 Rdis_{it} + \beta_7 Rirr_{it} + \beta_8 Rgra_{it} + \beta_9 Rpla_{it} + WX\theta + u_i + v_i + e_{it}$ (5)

where TFP represents the cumulative growth rate of agricultural TFP for individual I in year t, taking 2004 as the base year. W is the spatial weight matrix. The spatial weight matrix consists of the 0–1 matrix of 31 provinces in China.  $u_i$  is the individual effect;  $v_i$  is the time effect, and  $e_{it}$  is the error term. Taking the logarithm of variables can effectively reduce the collinearity problem and heteroscedasticity problem. Next you can see the description of the variables and data source from Table 4.

Table 4. Description of the variables in spatial Durbin model.

Variable	Definition	Data Source
TFP	the cumulative growth rate of agricultural TFP in each province	the results of DEA calculation
Urban	the proportion of permanent urban residents in each province	China Statistical Yearbook
Urban <sup>2</sup>	the square of Urban	China Statistical Yearbook
InPos	the logarithmic form of the internal R&D expenditure data in	China Statistical Yearbook on Science and
nines	each province	Technology
InMarkot	the logarithmic form of the degree of marketization in	Marketization Index of China's Provinces edited
IIIviaiKet	each province	by Xiaolu Wang
InL abor	the logarithmic form of the number of agricultural labor force in	China Rural Statistical Yearbook
IIILabol	each province	clinia Kalai Sudistical Tearbook
Rdis	the proportion of disaster sown area in each province	China Rural Statistical Yearbook
Rirr	the proportion of irrigated farmland in each province	Official Statistical Yearbook of each province
Rora	the ratio of the sown area of grain to the total sown area of crops	Official Statistical Vearbook of each province
Rgiu	in each province	Official Statistical Tearbook of each province
Rnla	the ratio of crop output value to total agricultural output values	Official Statistical Yearbook of each province
11pm	in each province	Sinchar Statistical Tearbook of each province

Due to data availability, the study uses the panel data of 31 provinces from 2004 to 2016. According to the classification standard of China Statistical Yearbook published by National Bureau of Statistics of China and existing research experience [56], 31 provinces are also divided into eastern, central and western regions in China for the analysis of regional heterogeneity, as shown in Table 5.

Regions	Provinces
Eastern region	Beijing, Tianjin, Hebei, Liaoning, Shanghai, Jiangsu, Zhejiang, Fujian,
Lastern region	Shandong, Guangdong, Guangxi, Hainan
Control region	Shanxi, Inner Mongolia, Jilin, Heilongjiang, Anhui, Jiangxi, Henan,
Central legion	Hubei, Hunan
Western region	Chongqing, Sichuan, Guizhou, Yunnan, Tibet, Shaanxi, Gansu, Qinghai,
Western region	Ningxia, Xinjiang

Table 5. 31 provinces in China.

#### 4. Results

4.1. Analysis of DEA Calculation Results

Figure 1 shows the dynamic evolution trend of technical efficiency change (TEC), technological progress (TP), pure efficiency change (PEC), scale efficiency change (SEC) and agricultural total factor productivity (TFP) from 2005 to 2016. Generally, a Malmquist index larger than 1 represents a positive TFP growth from t to t+1 [57] and TFP consists of TEC and TP. If the TEC is larger than 1, it means that the production of decision-making units is closer to the production frontier. Simultaneously, the variation in TC is positive with the movement of technical boundaries. Furthermore, TEC can be divided into PEC and SEC, which measures the variation in technology from the perspective of scale efficiency and pure technical efficiency.



**Figure 1.** The decomposition of the value of agricultural total factor productivity in China from 2005 to 2016.

From Figure 1, TP and agricultural TFP are greater than 1 in the whole period, which maintains the continuous and positive growth trend. Simultaneously the changing trend of TP and TFP are relatively similar. This shows that one of the main driving forces for the continuous improvement of agricultural production in China is agricultural technological progress, and the effect of TP is greater than that of TEC, which can be attributed to the overall movement of the agricultural production frontier, expanding the total capacity of the production efficiency. In some years, TEC is less than 1, and TP maintains a positive growth trend for a long time. The variation indicates that TEC deteriorated for a certain period and TP continues growing. China's agricultural technological progress has played a great role in promoting the growth of agricultural TFP. However, the agricultural technology has not been fully utilized, so there is a certain degree of efficiency loss.

rate of agricultural TFP is 4.8%. In order to analyze the long-term evolution trend of agricultural TFP, the calculation is based on 2004. In 2016, the cumulative growth rate of agricultural TFP reached 274.7%, which means that the cumulative growth rate of agricultural TFP increased by 2.747 times from 2004 to 2016. Further, it indicates that agricultural total factor growth can promote agricultural production in China effectively.

## 4.2. Analysis of Spatial Econometric Model

## 4.2.1. Analysis of Empirical Results

According to the estimated results in Table 6, the spatial autoregression coefficient (rho) is significant at the level of 1%. The coefficient value of rho is greater than 0, indicating that agricultural TFP has the positive spatial correlation. The spatial lag terms of W·Urban and W·Urban<sup>2</sup>, both pass the test at the significance level of 1%. The coefficient of Urban is negative, while the coefficient of Urban<sup>2</sup> is positive. It can be concluded that the impact of urbanization on agricultural TFP is significant and U-shaped. In addition, the spatial lag items, such as W·InRes, W·InMarket and W·InLabor, also pass the significance test, which indicates that InRes, InMarket and InLabor also have obvious spatial spillover effects on agricultural TFP.

Variable	Coefficient	<i>p</i> -Value	Variable	Coefficient	<i>p</i> -Value
Urban	-0.00303	0.419	W·Urban	-0.02796 ***	0.000
Urban <sup>2</sup>	0.00008 **	0.031	W.Urban2	0.00018 **	0.017
lnRes	0.03331	0.174	W·lnRes	0.25654 ***	0.000
lnMarket	-0.00352	0.851	W·lnMarket	0.11353 ***	0.003
lnLabor	0.01324	0.820	W·lnLabor	0.46814 ***	0.000
Rdis	-0.00006	0.811	W·Rdis	-0.00034	0.532
Rirr	0.00111	0.199	W·Rirr	0.00109	0.542
Rgra	0.01241 ***	0.000	W∙Rgra	0.00220	0.458
Rpla	0.00055	0.321	W∙Rpla	0.00189	0.108
rĥo	0.39286 ***	0.000	*		
sigma2_e	0.00393 ***	0.000			
Log-likelihood	517.86				

Table 6. The regression results of spatial Durbin model.

Note: \*\*\*, \*\*, and \* represent significance at 1, 5 and 10%, respectively.

Furthermore, spatial effect is usually decomposed into direct effect, indirect effect, and total effect. The total effect is the sum of direct effect and indirect effect [58]. The decomposition effect of SDM is shown in Table 7:

Table 7. The effect decomposition of spatial Durbin mode	el.
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Variable	Direct Effect	<i>p</i> -Value	Indirect Effect	<i>p</i> -Value	Total Effect	<i>p</i> -Value
Urban	-0.0060	0.121	-0.0445 ***	0.000	-0.0505 ***	0.000
Urban <sup>2</sup>	0.0001 ***	0.009	0.0003 ***	0.005	0.0004 ***	0.001
lnRes	0.0661 **	0.014	0.4259 ***	0.000	0.4920 ***	0.000
lnMarket	0.0079	0.680	0.1690 ***	0.004	0.1769 ***	0.010
lnLabor	0.0643	0.212	0.7414 ***	0.000	0.8057 ***	0.000
Rdis	-0.0001	0.746	-0.0006	0.474	-0.0007	0.469
Rirr	0.0012	0.196	0.0023	0.433	0.0036	0.313
Rgra	0.0132 ***	0.000	0.0114 ***	0.006	0.0246 ***	0.000
Rpla	0.0008	0.133	0.0031 *	0.086	0.0039 **	0.047

Note: \*\*\*, \*\*, and \* represent significance at 1, 5 and 10%, respectively.

In terms of direct effects, Urban is not significant, while Urban<sup>2</sup> passes the test at the significance level of 1%. Although the coefficient of Urban<sup>2</sup> is small, it still indicates that the impact of urbanization on agricultural TFP presents a U-shaped curve. LnRes is significant at the level of 5%. For every 1% increase in R&D expenditure, the growth of agricultural TFP will increase by 0.06%. Rgra is significant at the level of 1%. From the perspective of scale efficiency, large-scale production contributes to the improvement of agricultural production efficiency.

In terms of indirect effects, the coefficients of Urban and Urban<sup>2</sup> are, respectively, negative and positive, and both significant. This indicates that urbanization has a strong spatial spillover effect on agricultural TFP, which shows a U-shaped relationship; the spatial spillover effect of urbanization is obviously greater than the direct effect of urbanization. In the early stage of urbanization, the rapid development of urbanization will have a strong "siphon effect" on agricultural production factors. The siphon effect of urbanization leads to continuous rural-urban labor migration, investment transfer and occupied farmland, which hinders the growth of agricultural TFP. However, in the middle and late stage of urbanization, the spillover effect of urbanization on agricultural TFP is more significant, and the "trickle-down effect" is greater than the "siphon effect". The city pays more money and other productivity factors to the agricultural sector. The development of local urbanization will have a strong spatial spillover effect on the agricultural sector in the surrounding areas, which promotes the growth of agricultural TFP. At the same time, it can be noted that the spatial spillover effect of lnRes and lnMarket is far greater than the direct effect; the improvement of R&D and marketization is helpful to promote the efficiency of agricultural resource allocation so as to promote the growth of agricultural TFP.

In terms of total effects, Urban and Urban<sup>2</sup> are significant at the significance level of 1%, still showing the stable U-shaped curve relationship between urbanization and agricultural TFP. This also indicates that the impact of urbanization on agricultural TFP is negative first and then positive. In addition, R&D expenditure and the degree of marketization are significant on the overall effect. From the national level, the above independent variables have a promoting effect on agricultural TFP.

#### 4.2.2. Robustness Analysis

In order to ensure the robustness of the estimated results, in addition to using provincial 0–1 spatial weight matrix, the spatial weight matrix of economic distance constructed by provincial GDP is further used for SDM regression. The results are shown in Table 8. The spatial autoregressive coefficient  $\rho$  is significant at the significance level of 1%, which indicates a significant spatial dependence. The coefficient directions of Urban and Urban<sup>2</sup> are the same in the provincial 0–1 matrix and the economic matrix. These two variables pass the test in the case of direct effect and total effect, so the U-shaped curve relationship between urbanization and agricultural TFP growth can be verified.

Variable	Direct Effect	<i>p</i> -Value	Indirect Effect	<i>p</i> -Value	Total Effect	<i>p</i> -Value
Urban	-0.0110 **	0.043	-0.0163	0.101	-0.0274 ***	0.000
Urban <sup>2</sup>	0.0002 ***	0.002	0.0001	0.445	0.0002 ***	0.003
lnRes	-0.0301	0.252	0.1771 ***	0.009	0.1471 **	0.028
lnMarket	0.0471 **	0.021	-0.0937 *	0.097	-0.0466	0.426
lnLabor	0.0931	0.111	0.0027	0.983	0.0958	0.410
Rdis	-0.0002	0.425	0.0004	0.568	0.0002	0.814
Rirr	0.0022 **	0.029	0.0008	0.771	0.0030	0.245
Rgra	0.0154 ***	0.000	0.0017	0.688	0.0170 ***	0.000
Rpla	0.0010	0.114	-0.0045 ***	0.007	-0.0035 **	0.029
rho	-0.4854 ***	0.000				

Table 8. Regression results of spatial Durbin model in case of economic space weight matrix.

Note: \*\*\*, \*\*, and \* represent significance at 1, 5 and 10%, respectively.

As urbanization is a dynamic process, sometimes it does not directly affect agricultural production. Therefore, Urban\_lag (Urban of period t – 1) may have an effect on TFP of period t. In order to incorporate the lagging factors of urbanization into the model, the lagged variable of urbanization (Urban\_lag) and urbanization squared (Urban<sup>2</sup>\_lag) were selected as the core explanatory variables for the robustness test. The results of robustness test can be seen from Table 9. The spatial autoregressive coefficient  $\rho$  is significant at level of 1%, showing a strong spatial correlation. The new core explanatory variables (Urban\_lag) and (Urban<sup>2</sup>\_lag) are still significant in the direct effect, the indirect effect, and the total effect. In the case of the core explanatory variables lag behind, the impact of urbanization on agricultural TFP still shows a U-shaped curve. This shows that empirical results are robust. In addition, lnRes and lnMarket also show good consistency with the estimated results of Table 7. In the case of both indirect effect and total effect, the two variables passed the significance test, indicating that R&D investment and marketization have a strong positive spatial spillover effect of promoting agricultural TFP.

**Table 9.** The regression results of spatial Durbin model in the case of lagging core explanatory variables.

Variable	Direct Effect	<i>p</i> -Value	Indirect Effect	<i>p</i> -Value	Total Effect	<i>p</i> -Value
Urban_lag	-0.0066 *	0.095	-0.0394 ***	0.000	-0.0460 ***	0.000
Urban <sup>2</sup> _lag	0.0001 **	0.017	0.0003 ***	0.007	0.0004 ***	0.002
lnRes	0.0686 **	0.019	0.3766 ***	0.001	0.4452 ***	0.001
lnMarket	0.0141	0.454	0.1967 ***	0.001	0.2108 ***	0.002
lnLabor	0.0563	0.291	0.7924 ***	0.000	0.8487 ***	0.000
Rdis	-0.0002	0.561	-0.0005	0.527	-0.0007	0.474
Rirr	1.0545	0.288	1.5613	0.612	2.6157	0.477
Rgra	0.0124 ***	0.000	0.0082 **	0.075	0.0206 ***	0.000
Rpla	0.0006	0.249	0.0026	0.154	0.0033	0.104
rho	0.4063 ***	0.000				

Note: \*\*\*, \*\*, and \* represent significance at 1, 5 and 10%, respectively.

The above model regression results are based on the static panel model. However, there are still some problems in the static panel model, such as the inability to reflect the long-term interaction effect of dependent variables and the neglect of the influence of institutional and cultural factors. Generally, these factors are unavoidable. Therefore, the first-order lag term (lnTFP\_lag) of cumulative agricultural TFP can be used to capture the influence of these factors. The endogeneity problems of the static spatial panel model can be overcome to some extent by establishing dynamic spatial panel model. By comparing the regression results of dynamic panel model and static panel model, from Table 10 it can be found that the direction and significance of Urban and Urban<sup>2</sup> are basically similar in the case of indirect effect and total effect, except in the case of direct effect. This means that it is appropriate to analyze the impact of urbanization on agricultural TFP from spatial perspective and the impact shows a U-shaped curve. It is worth noting that the estimation coefficient of Urban is relatively smaller, maybe because the static panel model overestimates the impact of Urban and ignores the impact of cultural and institutional influences on agricultural TFP. As such, the dynamic panel model solves this problem relatively well.

## 4.2.3. Analysis of Regional Heterogeneity

According to the results of regional regression in Table 11, there are significant differences among the direct effect, indirect effect, and total effect of urbanization on agricultural TFP in eastern, central, and western regions in China.

Variable	Coefficient	<i>p</i> -Value	Variable	Coefficient	<i>p</i> -Value	
InTFP_lag	0.4750 ***	0.000	W * Urban	-0.0201 **	0.020	
W * Rdis	-0.0006	0.211	W * Urban2	0.0002 **	0.026	
W * Rirr	0.0010	0.518	W * lnRes	0.0694	0.188	
W * Rgra	-0.0084 ***	0.002	W * lnMarket	0.0578 *	0.074	
W * Rpla	0.0008	0.422	W * lnLabor	0.3755 ***	0.000	
rho	0.3615 ***	0.000				
Variable	Direct Effect	<i>p</i> -Value	Indirect Effect	<i>p</i> -Value	Total Effect	<i>p</i> -Value
Urban	0.0048	0.255	-0.0263 **	0.027	-0.0214 *	0.090
Urban <sup>2</sup>	0.0001	0.183	0.0004 **	0.016	0.0004 **	0.015
lnRes	-0.0097	0.684	0.0901	0.262	0.0804	0.399
lnMarket	-0.0099	0.532	0.0767	0.124	0.0668	0.250
lnLabor	0.0122	0.793	0.5365 ***	0.000	0.5487 ***	0.000
Rdis	-0.0002	0.304	-0.0009	0.188	-0.0012	0.141
Rirr	0.0015	0.044	0.0023	0.350	0.0038	0.195
Rgra	0.0061 ***	0.000	-0.0091 **	0.026	-0.0030	0.520
Rpla	-0.0005	0.250	0.0008	0.567	0.0003	0.866

 Table 10. Regression results of dynamic space panel model.

Note: \*\*\*, \*\*, and \* represent significance at 1, 5 and 10%, respectively.

 Table 11. Regression results of spatial Durbin model in the case of sub-regions.

Variable	Direct Effect	<i>p</i> -Value	Indirect Effect	<i>p</i> -Value	Total Effect	<i>p</i> -Value
Eastern						
Urban	-0.0113 *	0.098	-0.0119	0.358	-0.0231	0.208
Urban <sup>2</sup>	0.0002 ***	0.005	0.0000	0.794	0.0002	0.230
lnRes	0.0848 ***	0.009	0.0491	0.563	0.1339	0.180
lnMarket	-0.1584 **	0.043	0.2699	0.152	0.1115	0.634
lnLabor	-0.0307	0.557	0.5430 ***	0.000	0.5122 ***	0.000
Rdis	-0.0003	0.198	0.0000	0.999	-0.0003	0.576
Rirr	-0.0002	0.889	-0.0051 ***	0.009	-0.0052 **	0.033
Rgra	0.0144 ***	0.000	0.0018	0.520	0.0162 ***	0.000
Rpla	-0.0014 **	0.031	0.0017	0.193	0.0003	0.853
Central						
Urban	-0.0006	0.979	-0.1184 *	0.062	-0.1190	0.146
Urban <sup>2</sup>	0.0000	0.846	0.0010 *	0.083	0.0011	0.161
InRes	0.0974	0.110	0.0917	0.523	0.1891	0.328
lnMarket	-0.1475	0.397	-0.2405	0.421	-0.3880	0.296
lnLabor	-0.1550	0.426	0.5617	0.189	0.4067	0.449
Rdis	-0.0001	0.915	-0.0016	0.119	-0.0016	0.194
Rirr	0.0005	0.883	-0.0030	0.642	-0.0025	0.790
Rgra	0.0060	0.101	-0.0207 **	0.041	-0.0147	0.239
Rpla	0.0026 *	0.059	0.0047	0.108	0.0073 *	0.052
Western						
Urban	-0.0102	0.223	-0.0561 **	0.031	-0.0663 **	0.022
Urban <sup>2</sup>	0.0002 *	0.055	0.0011 ***	0.004	0.0014 ***	0.002
lnRes	-0.1759 ***	0.001	0.0774	0.631	-0.0984	0.570
lnMarket	-0.0040	0.875	-0.2600 **	0.082	-0.2641 *	0.086
lnLabor	0.3912 ***	0.004	1.9924 ***	0.000	2.3836 ***	0.000
Rdis	0.0001	0.816	-0.0005	0.795	-0.0003	0.876
Rirr	-0.0004	0.815	-0.0073	0.295	-0.0077	0.307
Rgra	-0.0075 *	0.061	0.0151	0.327	0.0077	0.636
Rpla	0.0027 *	0.058	-0.0008	0.802	0.0019	0.670

Note: \*\*\*, \*\*, and \* represent significance at 1, 5 and 10%, respectively.

From the perspective of the eastern region, the direct effect of urbanization is relatively significant, while the spatial spillover effect and the total effect are not significant. This may be related to the economic structure of major cities in the eastern region. For example, the first-tier cities such as Beijing, Shanghai, and Tianjin mainly focus on the secondary and tertiary industries and do not have enough resources to develop large-scale agricultural production. Therefore, the high-level development of urbanization has an obvious "crowding-out effect" on agricultural production, which is not conducive to the growth of agricultural TFP.

From the perspective of the central region, both urban and urban<sup>2</sup> pass the test at the significance level of 10%, showing the spatial spillover effect. Urbanization presents a U-shaped curve relationship with China's agricultural TFP but fails to pass the test in terms of direct effect and total effect. This may be related to the industrial policy and resource endowment of the central region.

From the perspective of the western region, both urban and urban<sup>2</sup> pass the test in terms of spatial spillover effect and total effect. There is a U-shaped curve between urbanization and agricultural TFP. The economic development of the western region is far behind that of the eastern and central regions due to historical and geographical factors. However, with the implementation of Western Development Strategy, the urbanization level and economic development level of the western region are steadily improving. Similarly, the spatial spillover effect of urbanization on agricultural TFP is also gradually increasing. However, the spatial spillover effect of lnRes and lnMarket is negative, which may be related to economic development mode and other institutional factors. For example, regional cooperation among provinces in the western region is relatively less, which further reduces the positive spatial spillover of lnRes and lnMarket.

#### 5. Conclusions and Recommendations

## 5.1. Conclusions

From 2004 to 2016, the average annual growth rate of agricultural TFP in China is 4.8%. It indicates that the growth of agricultural TFP may contribute to the enhancement of agriculture. Agricultural technological progress is one of the main forces to promote the growth of agricultural TFP in China, but scale efficiency index and technical efficiency index may restrain the growth of agricultural TFP to the extent.

At present, China's urbanization development and agricultural TFP growth have strong spatial spillover effects, and the spatial correlation effect is positive. The U-shaped curve of urbanization influencing the growth of agricultural TFP is significant on the direct effect, indirect effect, and total effect. This illustrates the impact and the degree of urbanization on agricultural TFP presents the dynamic change trend with the development stage of urbanization. Meanwhile, both the increase in R&D expenditure and the marketization degree are also important factors to promote the growth of agricultural TFP.

From the regional level of eastern, central and western regions, the impact of urbanization on agricultural TFP varies greatly in different regions due to the influence of economic development level, resource factor endowment and human geography factors.

## 5.2. Recommendations

A new pathway of urbanization should be followed. The Chinese government attaches great importance to the guiding role of urbanization in agricultural upgradation and takes measures such as absorbing surplus rural labor through urbanization, promoting the large-scale operation of agriculture, increasing policy support for agriculture to accelerate the modernization of agricultural production, which are conducive to the coordination of urbanization and modern agriculture.

While paying attention to the speed of urbanization development, the government should pay more attention to the quality of urbanization. From the perspective of sustainable coordination of urbanization and agricultural production, the siphon effect of urban on agriculture should be offset, while the "trickle-down effect" of cities on the agricultural

sector should be made full use of. Advanced science and technology, capital investment and efficient management experience in cities should be applied to agricultural production. The construction of agricultural infrastructure and the supply of agricultural input factors are guaranteed to the greatest extent, so as to ensure sustainable growth of agricultural TFP.

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