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Spatial-Temporal Pattern of Agricultural Total Factor Productivity Change (Tfpch) in China and Its Implications for Agricultural Sustainable Development

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Abstract: With increasing tension between humans and land, and arising pressure on food security in China, the improvement of total factor productivity is important to realize agricultural modernization and promote rural revitalization strategy. In this study, we applied the DEA-Malmquist index method to measure the growth of China's agricultural total factor productivity and its decomposition indexes at the prefecture-level city scale from 2011 to 2020. We found the average annual growth rate of agricultural total factor productivity was 4.5% during this period, with technical change being the driving factor and technical efficiency change being the suppressing factor. There is an initial decrease and then an increase in the Dagum Gini coefficient. The cold and hot spot areas of agricultural Tfpch were clearly formed. During the decade, the gravity center of agricultural Tfpch has migrated from the northeast to the southwest in general. Based on the characteristics of agricultural Tfpch, China is classified into four zones. In the future, the Chinese government should balance the government and the market mechanism, improve the agricultural science and technology innovation system and technology adoption promotion system, and implement classified policies to improve agriculture production efficiency.

Keywords: prefecture-level city scale; agricultural total factor productivity; spatial-temporal patterns; agricultural sustainable development

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1. Introduction

The improvement of overall agricultural productivity is important not only for promoting sustainable agricultural development but also ensuring the supply of agricultural products and food security [1]. Since the 21st century, the increasing population is placing unprecedented pressure on resources and the environment worldwide and adverse climate change is leading to low agricultural production efficiency [2]. Countries and regions around the globe are committed to improving agricultural productivity and promoting sustainable agricultural development [3]. If a country relies on international trade to ensure food security, the shock of the international food market will lead to the reduction in food supply, leading to soaring prices and food security risks [4].

Developing countries face greater pressure in this regard [5]. In China, since the reform and opening up, the nation has attached great importance to agricultural production; it has increased the input of agricultural production factors, resulting in remarkable achievements in agricultural development. Between 1978 and 2020, the total agricultural output value increased from 111.8 billion yuan to 717.48 billion yuan, and grain production increased from 304.77 million tons to 669.49 million tons. However, at the same time, China's agriculture is also facing problems such as a relatively extensive agricultural development model [6], a decrease in high-quality cultivated land resources [7], intensified constraints on resources and the environment, the loss of young and middle-aged labor [8], outstanding shortcomings in agricultural infrastructure [9], and insufficient support in agricultural science and technology [10]. These problems have led to weak growth of agricultural production efficiency, which has become a key bottleneck restricting high-quality agricultural development and even the advancement of the rural revitalization strategy [11,12]. Scientifically improving the input factor level, rationally optimizing the structure of the input factor, and improving agricultural total factor productivity have become major propositions.

The issue of agricultural total factor productivity has been highly considered by the government, and it is also a focus and hot spot in academic circles. There is a general consensus in the connotation of agricultural total factor productivity. It refers to the amount of production that can be increased when all the inputs of production factors are unchanged, and its purpose is to measure productivity excluding all the tangible factors of production. Related studies have explored agricultural total factor productivity using the growth accounting method [13], the DEA-Malmquist index method [14–16], and the stochastic frontier approach (SFA) method [16–19]. The DEA method and SFA method are commonly applied. The SFA method considers the impact of environmental changes and random factors on production behavior and can be carried out with statistical tests. The DEA method does not require defining the specific form of the production function in advance, so as to avoid the structural deviation caused by the wrong setting of production functions in traditional accounting methods such as the SFA method. The DEA method also does not require making a pre-determined assumption about the inefficiency distribution of the research sample. Therefore, the two methods both have advantages and disadvantages. The two methods will reach a relatively consistent conclusion in terms of numerical results [20–22]. However, most relevant studies about China apply the DEA method [23–25]. It shows that total factor productivity growth in China's agriculture has been driven by technical change and hindered by technical efficiency change [26,27], and the growth in eastern China is faster than that in central China and western China [27]. However, due to the difficulty in obtaining data, most of the studies were conducted on the provincial scale [28–30]. There is a lack of analysis of the spatial characteristics and temporal evolution patterns of agricultural total factor productivity on smaller scales [23]. In terms of the time period, most studies focus on before 2010 [28,31]. However, since 2010, especially since the 18th CPC National Congress, China has implemented a series of major strategies such as poverty alleviation and rural revitalization. Significant changes have taken place in the strategic objectives, policy system, and technical support of agricultural development. China's agriculture also has undergone deep changes. Agricultural development is changing from relying on resource input to being innovation-driven. Green ecological agriculture is developing rapidly. The reform of the agricultural land system is being implemented. There is a lack of long-term series follow-up studies on this issue.

This study aims to fill the gaps that few studies focus on 2011–2020 with radical changes and that few studies can be specific to prefecture-level city scale to explore more detailed spatial patterns.

In view of the large differences in the level and speed of agricultural development in various provincial administrative regions [23], this study is based on the panel data of agricultural output and input in prefecture-level cities from 2010 to 2020 and adopts the DEA-Malmquist index method model with national prefecture-level city scale. We analyzed the temporal evolution and spatial variation of agricultural total factor productivity change (Tfpch) in 359 prefecture-level cities across China by integrating the application of Dagum Gini coefficient, Moran's I, Getis-Ord G_i*, standard deviation ellipse, gravity center migration, and cluster analysis. We also proposed targeted regulation strategies aiming to provide support for the agricultural modernization development and the implementation of a rural revitalization strategy in China. Under the background of intensified resource and environment constraints and the complex and volatile international situation, this study aims to provide support for ensuring national food security by analyzing the implications for sustainable agricultural development.

2. Materials and Methods

2.1. Materials

The total agricultural output value (calculated at comparable prices in 1978) was selected as the output index based on the principles of scientificity, comprehensiveness and data availability, and considering the spatial-temporal comparative analysis of national prefecture-level city-scale data. The total sown area of crops was selected as the land input index. It means the area of actually sown or transplanted crops, which generally include food crops and cash crops. The number of employees in agriculture, forestry, animal husbandry and fisheries was selected as the labor input index. It can better reflect the actual use of an industry in a certain period than the economically active population and unit employment. The total power of agriculture machinery was selected as the capital input index. It was defined as the sum of the power of various kinds of power machinery mainly used in agriculture, forestry, animal husbandry and the fishery industry in that year. The consumption of chemical fertilizers in agriculture, that is, the actual amount of fertilizer used in agricultural production in that year was selected as the intermediate input index.

The study data came from the statistical yearbooks and agricultural and rural yearbooks of each province, autonomous region and municipality directly under the central government from 2010 to 2020. The statistical descriptions of relevant output and input indexes were shown in Table 1.

Table 1. Statistical description of output and input indexes.

Statistics	Total Agricultural Output Value (Million Yuan)	Total Sown Area of Crops (Thousand Hectares)	Consumption of Chemical Fertilizers in Agriculture (Million Tons)	Total Power of Agriculture Machinery (Million Kilowatts)	The Number of Employees in Agriculture, Forestry, Animal Husbandry and Fishery (Persons)
Average	2401.670	611.364	15.596	2623.391	718,304.258
Median	1961.668	354.361	10.641	203.308	610,302
Maximum	23,249.818	471,304.900	97.730	6,249,295	6,261,200
Minimum	5.077	0.289	0.001	0.162	61
Standard deviation	2054.968	7819.627	15.354	106,497.230	620,524.767
Sample numbers	3949	3949	3949	3949	3949

2.2. Methods

2.2.1. DEA-Malmquist Index Method

This study applied the DEA-Malmquist index method to calculate the total factor productivity. The DEA-Malmquist index method uses a distance function to construct a production frontier and thus measure the rate of change in production efficiency. The principle is to first calculate the Malmquist index with technical conditions in period t as the reference:

$$M_t(X_t, Y_t, X_{t+1}, Y_{t+1}) = \frac{D^t\left(X^{t+1}, Y^{t+1}\right)}{D^t(X^t, Y^t)} \tag{1}$$

In Equation (1), D represents the distance function and (X, Y) represents the input-output vector in a specific period. Similarly, the Malmquist index for the technical conditions in period $t + 1$ can be calculated as:

$$M_{t+1}(X_t, Y_t, X_{t+1}, Y_{t+1}) = \frac{D^t\left(X^{t+1}, Y^{t+1}\right)}{D^t(X^t, Y^t)} \tag{2}$$

The geometric mean of Equations (1) and (2) is then used as the Malmquist index from period t to period $t + 1$:

$$M(t+1) = \left[\frac{D^t\left(X^{t+1}, Y^{t+1}\right)}{D^t\left(X^t, Y^t\right)} \times \frac{D^t\left(X^{t+1}, Y^{t+1}\right)}{D^t\left(X^t, Y^t\right)} \right]^{\frac{1}{2}} \tag{3}$$

The results of the Malmquist index take into account the non-technical efficiency change in the production process. Under the premise of constant returns to scale (CRS), the Malmquist index (Tfpch) can be divided into technical change (Techch) and technical efficiency change (Effch):

$$\text{Tfpch} = \text{Techch} \times \text{Effch} \tag{4}$$

Under the premise of variable returns to scale (VRS), technical efficiency change can be further divided into pure technical efficiency change (Pech) and scale efficiency change (Sech):

$$\text{Effch} = \text{Pech} \times \text{Sech} \tag{5}$$

Specifically, in the field of agricultural production, a Malmquist index >1 represents agricultural production efficiency has increased compared with the previous comparison period. A Malmquist index < 1 represents agricultural production efficiency that has decreased compared with the previous comparison period. A Malmquist index = 1 represents agricultural production efficiency that is flat compared with the previous comparison period. Among indexes in Equations (4) and (5), technical change means the outward shift of the production frontier, that is, technical progress yields more output for the same input. Technical efficiency change refers to the improvement of resource utilization efficiency by improving the coordination of various agricultural input resources (e.g., land, capital, labor, etc.) under the conditions of the existing technology level, which brings agricultural production closer to the production frontier [14].

2.2.2. Dagum Gini Coefficient

Compared with the traditional Gini coefficient, Thiel's index, and so on, the Dagum Gini coefficient G [32] is able to measure the sources of regional differences and the accuracy of the conclusions is higher, by taking account of the overlapping of sub-samples and their distribution. In this study, the Dagum Gini coefficient G was applied to measure the spatial variation and sources of agricultural Tfpch in China.

$$G = \frac{\sum_{j=1}^{k} \sum_{h=1}^{k} \sum_{i=1}^{n_j} \sum_{r=1}^{n_h} \left| y_{ji} - y_{hr} \right|}{2n^2 \mu} \tag{6}$$

$$G = G_w + G_{nb} + G_t \tag{7}$$

According to Equation (6), the overall variation of agricultural Tfpch in China can be obtained, where y_{ji} (y_{hr}) represents the value of agricultural Tfpch of any prefecture-level city in the j(h) region, n represents the number of all prefecture-level cities in China, μ represents the mean value of agricultural Tfpch in China, and $k = 4$ (that is the number of regions divided in this study). As shown in Equation (7), Dagum Gini coefficient G can be decomposed into intra-regional differences G_w, inter-regional differences G_{nb}, and intensity of transvariation G_t.

2.2.3. Spatial Autocorrelation Analysis

Global spatial autocorrelation analysis was applied to analyze the clustering degree of the Malmquist index. Moran's I is one of the commonly used measures, which is calculated as:

$$I = \frac{\sum_{i=1}^{n} \sum_{j=1}^{n} W_{ij}(Y_i - Y)}{\sum_{i=1}^{n} (Y_i - Y)^2} \tag{8}$$

In Equation (8), Y_i denotes the Malmquist index of a prefecture-level city i, Y_j denotes the Malmquist index of prefecture-level city j, n is the number of prefecture-level cities, Y is the average value of the Malmquist index, and W_{ij} is the spatial weight matrix. $I > 0$ means that the Malmquist index has an overall positive correlation in space, that is, prefecture-level cities with high or low values are clustered. $I = 0$ means that the Malmquist index is randomly distributed in space. $I < 0$ means that the Malmquist index has an overall negative correlation in space.

To further determine the exact locations where high- or low-value elements are spatially clustered, Getis-Ord G_i* is applied. It is calculated by the formula:

$$G_i^* = \frac{\sum_{j=1}^{n} W_{ij}(X_j - \bar{X})}{S\sqrt{\frac{\left[n\sum_{j=1}^{n} W_{ij}^2 - \left(\sum_{j=1}^{n} W_{ij}\right)^2\right]}{n-1}}} \tag{9}$$

In Equation (9) W_{ij} is the spatial weight matrix, X_j is the Malmquist index of prefecture-level city n, X is the mean value of all prefecture-level cities' Malmquist indexes, and n is the number of prefecture-level cities. G_i* > 0 means that the area is a hot spot area. G_i* < 0 means that the area is a cold spot area. G_i* = 0 means that the result is randomly generated. Significance tests were performed on the G_i* values to obtain the cold and hot spot areas with confidence intervals.

2.3. Theoretical Framework

The theoretical framework of this study is shown in Figure 1. This study selected the input and output indexes mentioned above for DEA. Tfpch and its decomposition indexes can be obtained by applying the DEA method. Then, this study used Dagum Gini, Moran's I, Getis-Ord G_i*, standard deviation ellipse and mean center to analyze spatial-temporal patterns for promoting agricultural sustainable development.

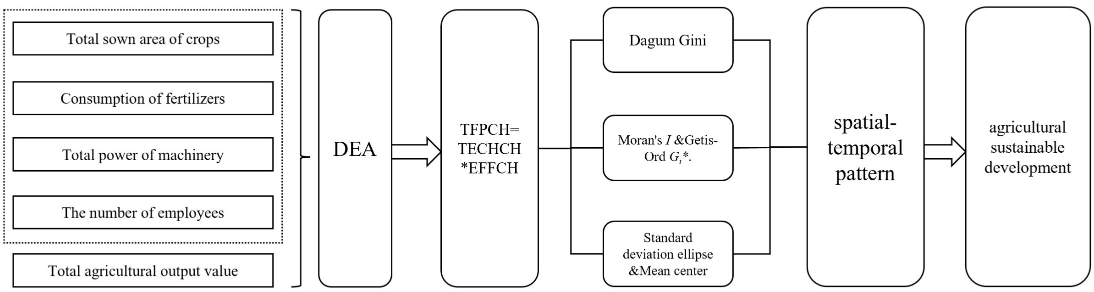

Figure 1. The theoretical framework of this study.

3. Results

3.1. Temporal Variation Patterns of Total Factor Productivity in Agriculture

As shown in Table 2, the total agricultural factor productivity of China has continued to rise in general. From 2011 to 2020, the average national agricultural Tfpch is 1.045, with an average annual growth of 4.5%. Except for 2017, the agricultural Tfpch is greater than 1 in other years. This increase in agricultural output not brought about by the increase in input factors is closely related to China's high emphasis on agricultural production and a series of agricultural protective and incentive policies implemented under the WTO framework, which are represented in the market price protection for agricultural products and income support for agricultural workers. At the same time, the improvement of farmers' education level and technical training levels has effectively driven the increase in agricultural total factor productivity [33]. In addition, the continuous improvement of China's opening-up, on the one hand, enables China to import agricultural production factors at lower prices. On the other hand, China can introduce and transform a number of foreign advanced agricultural production methods and production technologies, so as to promote the improvement of agricultural Tfpch [34]. The increasing investment in scientific research, especially in agriculture scientific research, also plays an important role in the improvement of agricultural total factor productivity [35].

Table 2. Agricultural Tfpch and its decomposition indexes in China, 2011–2020.

Year	Tfpch	Techch	Effch	Pech	Sech
2011	1.050	0.995	1.055	0.973	1.084
2012	1.064	1.067	0.997	1.084	0.919
2013	1.047	1.094	0.957	0.97	0.987
2014	1.039	1.059	0.981	0.982	0.999
2015	1.033	1.051	0.983	0.962	1.021
2016	1.043	1.009	1.034	1.026	1.008
2017	0.976	0.962	1.014	0.931	1.090
2018	1.062	1.221	0.870	0.962	0.905
2019	1.078	1.021	1.056	1.045	1.010
2020	1.059	1.116	0.949	1.036	0.916
Average	1.045	1.057	0.988	0.996	0.992

In terms of the decomposition indexes of agricultural Tfpch, this study finds a trend of enhanced technical change and weakened technical efficiency change, which is worthy of attention. The increase in agricultural total factor productivity is mainly driven by technical change. The growth of technical change outweighs the decline of technical efficiency change. The growth of total factor productivity in agriculture mainly comes from the movement of the agricultural production frontier rather than the approach to the agricultural production frontier, which reflects that the utilization efficiency of input factors in China's agricultural production needs to be improved, and agricultural technology adoption needs to be promoted in the near future.

In terms of scale efficiency change, the scale efficiency change of agricultural production in China is less than 1 in general. There is a phenomenon of weakening scale efficiency during the decade. It has resulted from China investing heavily in agricultural production with the goal of ensuring national food security, but it is difficult to expand the area of agricultural land [36], especially cultivated land, and the scale of agricultural production grows slowly (Table 2). The weakened scale efficiency of agricultural production also confirms from the opposite side the necessity of continuously deepening the reform of the rural land system and promoting moderate large-scale management of land in China [37].

3.2. Spatial Variation Patterns of Total Factor Productivity in Agriculture

3.2.1. Spatial Variation in Total Factor Productivity

The agricultural Tfpch shows significant spatial variation characteristics, affected by differences in agricultural resources, agricultural policies, industrial structure, and economic development conditions in prefecture-level cities (Figure 2).

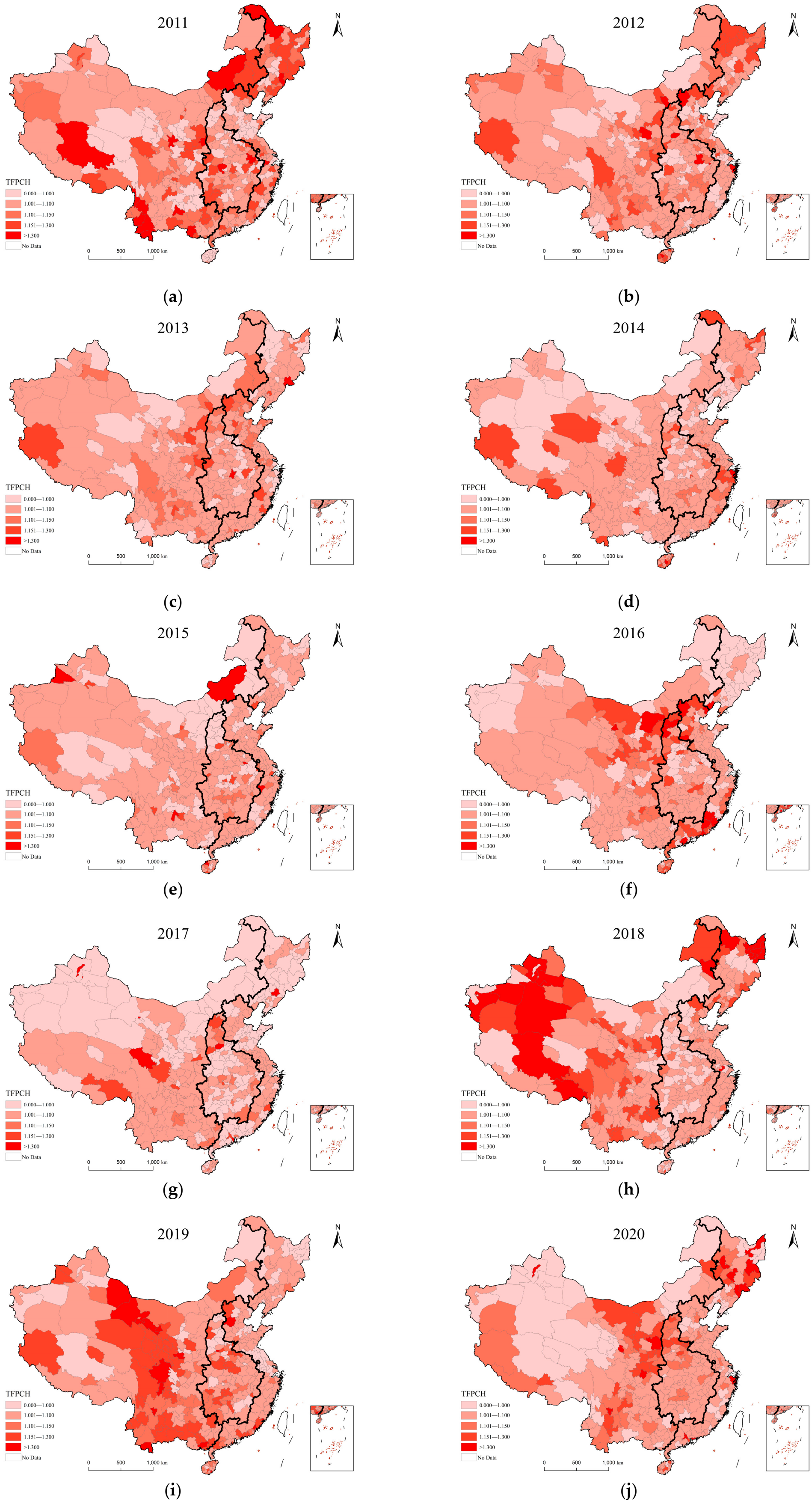

Figure 2. Agricultural Tfpch of prefecture-level cities in 2011 (**a**), 2012 (**b**), 2013 (**c**), 2014 (**d**), 2015 (**e**), 2016 (**f**), 2017 (**g**), 2018 (**h**), 2019 (**i**) and 2020 (**j**).

The agricultural Tfpch in four major regions (Table 3) shows the spatial characteristics of western China > eastern China > central China > northeast China. Specifically, it is the highest in western China. First, the natural endowment of resources and the environment in this region is relatively poor, and its agricultural development foundation is also weak. In recent years, advanced agricultural technologies and typical models have been introduced, resulting in a significant "latecomer advantage" in this region [38]. Second, under the background of comprehensively promoting a targeted poverty alleviation strategy, compared with eastern, central, and northeast China, western China has generally received a series of more favorable poverty alleviation programs, such as the East-West poverty alleviation collaboration twinning relationship and poverty alleviation collaboration through enterprise cooperation [39]. Furthermore, natural disasters, especially geological disasters, are frequent in the western region. Natural disasters restrain the upgrading of agricultural production technology, but their consequences often lead to an increase rather than a decrease in agricultural infrastructure such as water conservancy facilities and rural roads, thereby promoting the agricultural total factor productivity by improving technical efficiency change [28].

Table 3. Agricultural Tfpch and its decomposition factors in four major regions of China.

Region	Tfpch	Techch	Effch	Pech	Sech
China	1.045	1.057	0.988	0.996	0.992
Northeast China	1.034	1.059	0.977	0.985	0.991
Eastern China	1.040	1.056	0.984	0.992	0.992
Central China	1.040	1.058	0.983	0.991	0.992
Western China	1.057	1.058	1.000	1.007	0.992

Generally speaking, eastern China is endowed with superior resources such as water, heat, and terrain for agricultural production. Its strong ability to radiate external urbanization and industrialization, and the increasingly formed pattern of complementary functions and urban-rural integration have directly led to the improvement of agricultural production efficiency. However, at the same time, problems such as insufficient water supply, water pollution [40], and soil pollution [41] occurred sometimes, which need to be effectively addressed to ensure the sustainable improvement of agricultural production efficiency.

Central China is an important grain-producing region, and the proportion of agricultural employees to the total number of employees is higher than the national average. The proportion of rural surplus labor is large, and it is difficult to transfer to other industries, resulting in the restriction of agricultural land circulation and moderate large-scale management, which limits the improvement of agricultural total factor productivity [42].

As an important grain-producing region, northeast China has a long history of agricultural production and mature agricultural production technology. However, in recent years, the population, especially middle-aged labor, has been seriously lost [23] and its potential for further improvement in agricultural productivity is limited. This results in a high level of agricultural development, but the development speed lags behind other regions.

From the perspective of China's four major economic regions, the four regions were all "technically driven". Technical change (Techch) drove the improvement of agricultural total factor productivity, while technical efficiency change (Effch) hindered the improvement of agricultural total factor productivity. Further decomposition of the technical efficiency change (Effch) showed that only the pure technical efficiency change (Pech) in western China has increased, while all the other three regions showed a decline. The change in scale efficiency change (Sech) of the four regions all showed a downward trend, and the differences among regions were small.

The Dagum Gini coefficient was applied to measure the Gini coefficient of both China and four major regions during 2011–2020. The results showed an initial decrease and then an increase in the Gini coefficient of Tfpch. With the government's policy support for underdeveloped regions, regional differences in agricultural development may decrease in some years, but there are large differences in natural elements such as sunlight, heat, water source and soil fertility in different regions [43]. Regional differences have been expanding since 2014, showing that there is still room for improvement in regional coordination of agricultural development.

During the study period, the contribution ratio of the intensity of transvariation was the largest, with an average of 64.53%, followed by the contribution ratio of intra-regional differences, with an average of 24.80%. The contribution ratio of inter-regional differences was the smallest, with an average of 10.65%. The contribution ratio of the intensity of transvariation to the overall differences of agricultural Tfpch in China remains at a high level. On the one hand, it represented a large number of "ungrouped" prefecture-level cities that split off from their groups into higher or lower groups. For example, in 2020, the level of agricultural Tfpch in northeast China was higher than in eastern, central and western China, but the agricultural Tfpch value in prefecture-level cities such as Jixi, Tieling, and Anshan was all less than 1, ranking at the bottom. On the other hand, the intensity of transvariation reflected the contribution of overlap between subsamples to the overall difference [44], which accounted for a high proportion in this study. This means there exist significant differences in agricultural development levels within the four major economic regions, and spatial mismatch between the division of economic regionalization and agricultural regionalization (Figures 3 and 4).

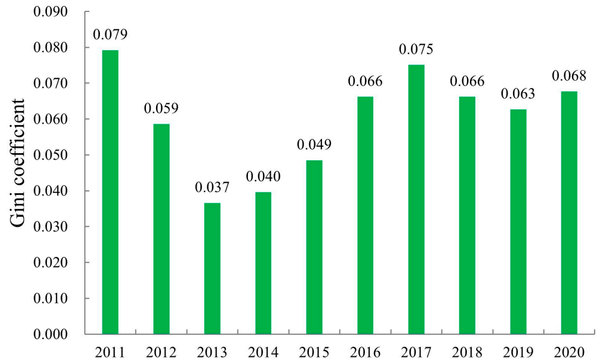

Figure 3. Gini coefficient of agricultural Tfpch during 2011–2020.

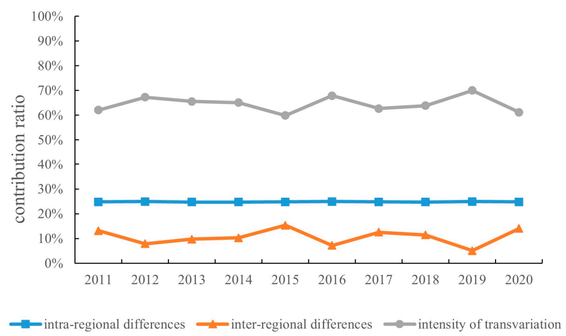

Figure 4. Decomposition contribution ratio of Gini coefficient of agricultural Tfpch during 2011–2020.

3.2.2. Spatial Correlation of Agricultural Tfpch

This study analyzed the spatial correlation degree and the specific locations of spatial agglomeration of agricultural Tfpch from global and local perspectives by using Moran's *I* and Getis-Ord G_i*.

According to the panel data, the Moran's *I* index and its determination coefficient (Table 4) showed that the Moran's *I* index in 2015 was statistically significant at the 5% significance level. The Moran's *I* indices for 2011–2014 and 2016–2019 were statistically significant at the 1% significance level. The index in 2020 did not pass the significance test. The values of Moran's *I* from 2011 to 2020 were all greater than 0. Agricultural Tfpch at the prefecture-level city scale presented characteristics of spatial agglomeration in most years, which was related to the high similarity of agricultural production conditions such as natural resource endowment in adjacent prefecture-level cities.

Table 4. Spatial autocorrelation test of agricultural Tfpch.

Year	Moran's *I*	Z	P
2011	0.146 [1]	11.149	0.001
2012	0.038 [1]	3.426	0.001
2013	0.105 [1]	8.108	0.001
2014	0.176 [1]	13.304	0.001
2015	0.029 [2]	2.547	0.010
2016	0.071 [1]	5.690	0.001
2017	0.068 [1]	5.373	0.001
2018	0.112 [1]	9.033	0.001
2019	0.107 [1]	8.346	0.001
2020	0.015	1.390	0.164

[1] and [2] represent significant at the statistical level of 1% and 5%, respectively. Z scores represent standard deviations. P values represent the probability that the observed spatial pattern is created by a random process.

The analysis of agricultural Tfpch Getis-Ord G_i* (Figure 5) showed that hot spots were concentrated in southwest areas, such as the Yunnan-Guizhou Plateau, Sichuan Basin, and Hengduan Mountains, which were directly related to a series of poverty alleviation measures taken in recent years [39]. The cold spots were mainly distributed in northeast China, North China Plain and southern Xinjiang. Among them, the agricultural development foundation in northeast China was better, but the development speed was slower. The North China Plain was located in the Huang-Huai-Hai Plain, with superior natural and geographical conditions. However, due to the obvious trend of a non-agricultural labor force, especially the young and middle-aged labor force, in addition to the shortage of water resources in recent years [45], the agricultural output increase was curbed.

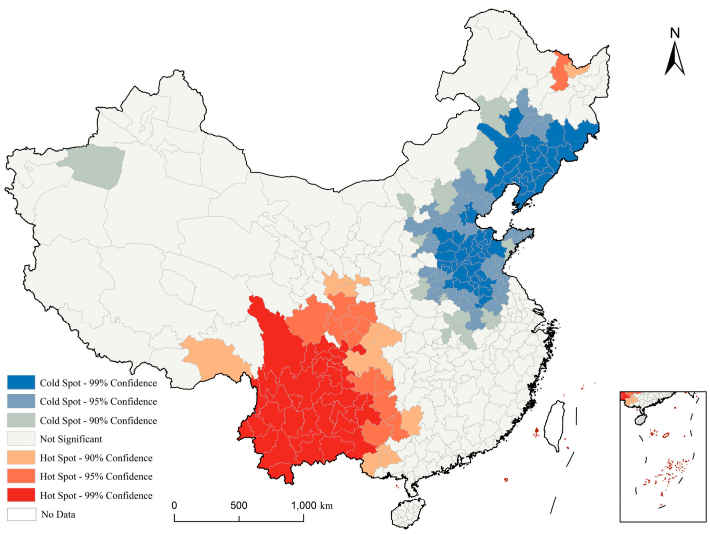

Figure 5. Getis-Ord G_i* of agricultural Tfpch in China.

3.2.3. Spatial Migration of Agricultural Tfpch

To further reveal the spatial variation characteristics of agricultural Tfpch in 359 prefecture-level cities across China, the standard deviation ellipse and the migration trajectory of its gravity center were visually represented via ArcGIS 10.8 software (Figure 6). During the study period, the spatial distribution of agricultural Tfpch in China showed an overall pattern of "northeast-southwest". The gravity center of agricultural Tfpch migrated within Nanyang, Henan Province and Xiangyang, Hubei Province, with an offset of about

52 km from northeast to southwest. The gravity center was far from the geometric center of China, indicating a disequilibrium in the spatial distribution of agricultural Tfpch. This migration of the gravity center supports the above-mentioned hot spot area of agricultural Tfpch in the western region of China from another perspective. It is worth noting that the agricultural production in eastern and northeast China was not inefficient, but the overall developing speed was relatively behind western China, forming a relatively cold spot area. At the same time, this further confirmed the findings that agricultural TFP grew faster in eastern and northeast China than in western China before 2010 [46] and that agricultural TFP grew faster in western than in eastern or northeast China since 2010 [30].

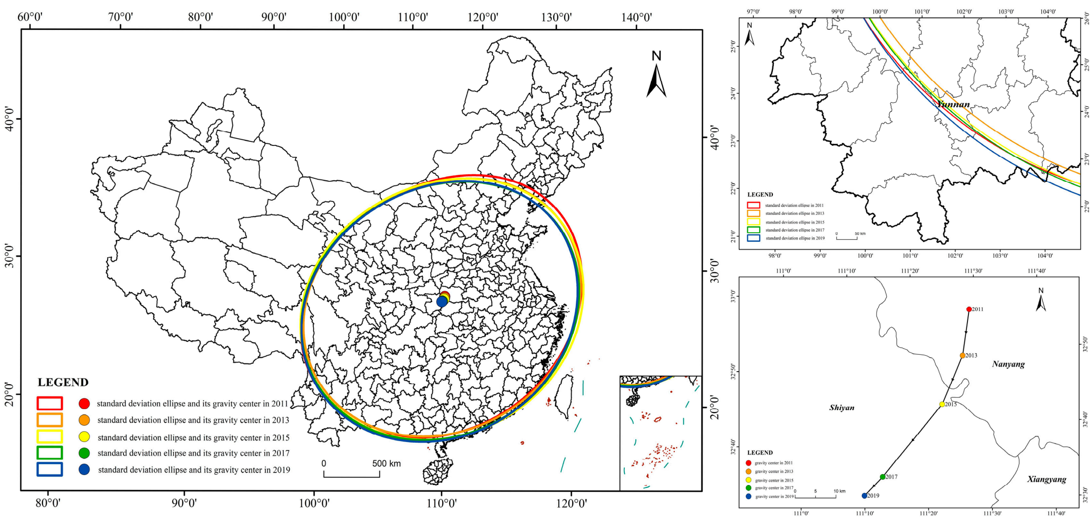

Figure 6. Standard deviation ellipse of agricultural Tfpch and its gravity center migration trajectory.

3.3. Agricultural Tfpch Clustering

We took the prefecture-level city as a basic unit, combining it with the values of three indexes of agricultural total factor productivity change (Tfpch), technical change (Techch), and technical efficiency change (Effch), and then applied the K-means clustering method in SPSS 16.0 software for type classification. Here are the resulting four types (Figure 7):

(1) High Tfpch-technical change and technical efficiency change double-wheel-driven cities (total of 21). This type was of very small number and sporadic distribution across China. Most of them were in underdeveloped areas, but their agricultural total factor productivity grew rapidly driven by the double-wheel-drive of technical change and technical efficiency change.

(2) Low Tfpch-technical efficiency change hindered cities (total of 49). This type was very few. Most of them were distributed in the interprovincial fringe areas in northwest, north and northeast China. These cities have poor natural conditions and low transportation accessibility, which limit the application of advanced agricultural technologies. In addition to administrative barriers between regions, the flow and optimal allocation of agricultural production factors were also restrained. It is crucial to strengthen infrastructure construction (e.g., transportation) and establish a regional coordination mechanism [47].

(3) Medium Tfpch-technical change and technical efficiency change double-wheel-driven cities (total of 124). The number of this type was large, and the decomposition indexes of agricultural Tfpch were relatively balanced. Most of them are distributed in south China, especially in southwest China.

(4) Medium Tfpch-technical change single-wheel-driven cities (total of 165). The number of this type was the largest. These cities are spread over most provinces, most of which are located in north China, northwest China and the Qinghai-Tibet region. The improvement of agricultural total factor productivity in such prefecture-level

cities was mainly driven by technical change, but the promotion of agricultural technology adoption was limited. To realize the two-wheel-driven technical change and technical efficiency change and improve agricultural total factor productivity, the Chinese government should put efforts in the following aspects: the improvement of the agricultural technology adoption promotion system at the grassroots level, the enhancement of agricultural technology adoption promotion institutions to provide precise services with modern technology tools such as the Internet and artificial intelligence [48], and the promotion of the popularity of agricultural technology services [29,37].

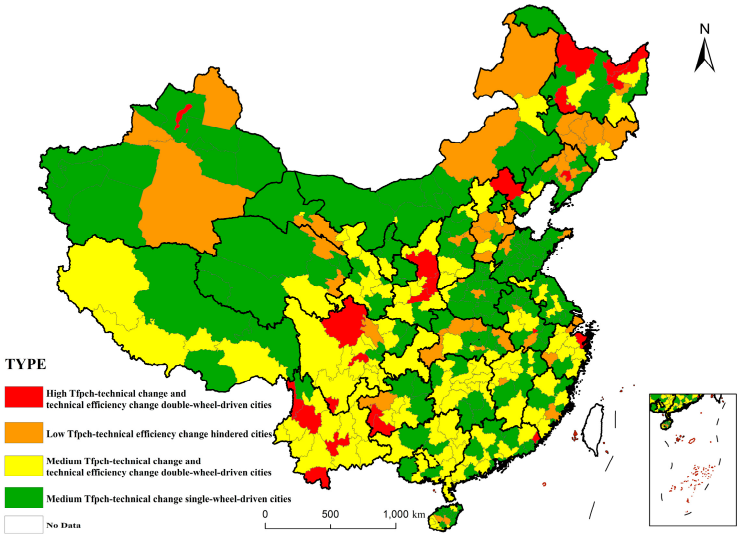

Figure 7. Four types of Agricultural Tfpch spatial clustering analysis.

4. Discussion

4.1. New Findings from the Study

As mentioned earlier, most relevant studies [28,31] concentrated on the time period before 2010, and mainly on how the scale efficiency change can promote the growth of agricultural TFP. In this study, the scale efficiency change hindered the growth of agricultural TFP in recent years, implying the urgency of implementing moderate large-scale management of land. This was mainly because after 2010, all the input factors of China's agricultural production grew rapidly except the land factor, making it difficult to promote moderate large-scale management of land.

Most the relevant studies [42,46] before 2010 concluded that the growth of agricultural TFP in eastern China was faster than in western China. This was because government agricultural policies before 2010 were more inclined to improve efficiency, and eastern China, which has better natural conditions for agricultural production, was able to obtain more favorable policies. While agricultural policies after 2010 were more inclined to coordinate regional development and equity [27]. The level of agricultural development in western China was relatively low, thus it was able to obtain more favorable policies. Western China made full use of policies to stimulate the "latecomer advantage" and has the fastest agricultural TFP growth, suggesting that besides natural conditions, government policies played an important role in agricultural production efficiency growth.

4.2. Implications for Sustainable Agricultural Development in China

First, efforts should be made to optimize the flow and allocation of agricultural production factors through the balance between the government and the market mechanism. China should give full play to the administrative power of local governments, explore the establishment of regional coordination mechanisms, and break down the institutional barriers that hinder the cross-regional flow of production factors such as agricultural technology and labor [49,50]. Especially, low Tfpch-technical efficiency change hindered cities in the interprovincial fringe areas; in order to narrow regional differences and promote the coordinated development of urban and rural areas, it is necessary to break down the established administrative barriers, establish the concept of "one chessboard", coordinate and cooperate in the allocation of agricultural production factors to achieve complementary advantages and development integration. It is essential to deepen the reform of "streamlining administration, decentralization, and optimizing government services ", reduce the institutional costs of agricultural production factor transactions, promote inter-regional agricultural technology exchange and the flow of agricultural talents, and improve agricultural infrastructure in backward areas. A study [51] in 17 major agriculture-producing countries mentions that government efficiency and government policy reform are important for promoting agriculture production efficiency.

Second, it is advised to promote "two-wheel-driven" technical change and technical efficiency change. China should improve the agricultural science and technology innovation system, increase the investment in agricultural science and technology research and development, and focus on the research and development of improved varieties and intelligent agricultural machinery [30]. The organization system and work system of agricultural technology adoption promotion should be also improved. In order to improve the suitability and conversion rate of new agricultural technology, especially in the medium Tfpch-technical change single-wheel-driven cities, two transformations should be realized: the transformation of the agricultural technology adoption promotion mechanism from "top-bottom" supply-oriented to demand-oriented, and from a government-led unitary system to an integrated system comprising government, family farms, agricultural cooperatives, large farmers, third-party service agencies and so on. A study [52] in the Republic of Malawi also points out that the number of promotion educators is essential for agricultural technology adoption promotion.

Third, China should promote efficient agricultural production and coordinated socioeconomic development based on regional function positioning. It is essential to distinguish different types of areas and implement policies according to local conditions. Areas that are dominated by agricultural production should develop mechanized production, large-scale operations, and market-oriented sales. They are expected to actively explore the path of agricultural modernization and guarantee national food security [53]. Areas that dominated by urbanization and industrialization development should cultivate modern high-end agricultural science and technology talents, increase modern agricultural science and technology innovation, focus on developing capital-intensive and technology-intensive agriculture, and promote the development of high-quality agriculture and intelligent agriculture models. In areas dominated by ecological function protection, they should balance between protection and development, strictly control the use of pesticides and chemical fertilizers, and actively develop green agriculture and ecological agriculture to improve the market competitiveness of agricultural products [54]. A study [55] in the European Union also attaches great importance to classification and implementing policies according to local conditions.

4.3. Limitations and Prospects of this Study

This study provided a qualitative analysis of the variation in spatial-temporal patterns of agricultural Tfpch. Influenced by the difficulties in collecting data at the prefecture-level city scale, no further quantitative analysis has been conducted on the drivers of spatial and temporal variation. In addition, this study used total agricultural output value as the output index, which was a compromise made to unify the output of different types of crops. In fact, the outputs of different types of crops are very complex, and it is extremely difficult to uniformly quantify their output values. However, considering the small differences in market prices of major crops across China, it has little impact on the study of the national spatial-temporal pattern.

Future studies will focus on Chinese spatial differentiation of agricultural potential and explore whether it is positively or negatively correlated with natural conditions, economic factors and so on [56,57]. In addition, combining remote sensing data with statistical yearbooks and taking international trade into consideration in the future can be more convincible [52,58].

5. Conclusions

Based on the panel data of agricultural inputs and outputs of 359 prefecture-level cities across China from 2010 to 2020, this study measured their agricultural Tfpch using the DEA-Malmquist index method, analyzed the temporal evolution pattern of China's agricultural Tfpch and its decomposition indexes during this period. This study applied the Dagum Gini coefficient, Moran's I, Getis-Ord G_i*, standard deviation ellipse, migration of gravity center, etc., to reveal its spatial pattern and driving factors from different perspectives. The study findings are as follows.

(1) China's agricultural TFP on the prefecture-level city scale kept growing from 2011 to 2020, with an average annual growth rate of 4.5%. The technical change was an important driver of China's agricultural TFP growth, while technical efficiency change played a hindering role in general. Technical change can help reduce the harm of risks, especially climate risks [58].
(2) The spatial variation of China's agricultural Tfpch was significant, with the western, eastern, central and northeast China in descending order. The higher growth rate in western China represented a good momentum of rapid agricultural development there and the improving coordination of regional agricultural production. However, compared with the long-term accumulated agricultural advantages in eastern and northeast China, western China needs to maintain this good momentum to continue to catch up. The Dagum Gini coefficient shows that the intensity of transvariation contributes most to regional differences. Significant spatial autocorrelation existed in China's agricultural Tfpch, and there was a clear division of hot and cold between the northeast and southwest regions. As the highland of China's agricultural production, northeast China needs urgent attention to increase the growth rate of agricultural production efficiency. Northeast China should make full use of the advantage of global temperature rise, which is more beneficial for high-latitude regions in agriculture production [2,59].
(3) The spatial distribution of agricultural Tfpch presented an overall "northeast-to-southwest" pattern, and the gravity center generally moved from the northeast to the southwest. The rapid rise of the southwest has a positive significance for the balanced development of regional agriculture in China. However, under the objective situation of relatively poor endowment conditions of agricultural land resources such as cultivated land and a fragile ecological environment, it remains to be seen whether this rapid growth momentum can be sustained in the southwest region.

The above conclusions will provide a reference for the agricultural policies of the Chinese government. The government should focus on not only agricultural technology innovation but also agricultural technology adoption promotion. After the completion of a targeted poverty alleviation strategy, the government is supposed to reconsider the policy of regional agriculture coordinated development.

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