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# Spatiotemporal Heterogeneity of Total Factor Productivity of Grain in the Yangtze River Delta, China

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**Abstract:** The total factor productivity of grain (TFPG) is critically important to secure food production, while its spatiotemporal heterogeneity in the urbanized area is largely ignored. Selecting 41 cities in the Yangtze River Delta, this study uses the data envelopment analysis (DEA) Malmquist index method to measure the TFPG in each city from 2012 to 2020 based on panel data, and explores the driving factors of the spatiotemporal evolution of the TFPG with the geographically and temporally weighted regression model. The results indicate the following: (1) Both the TFPG and technological progress varies in the same direction, indicating that technological progress dominates the TFPG in the studied region. The changes in technical efficiency, pure technical efficiency, and scale efficiency are relatively stable. (2) The spatial distribution of the TFPG shows a decentralized trend, with a pattern of high in the north and east areas and low in the south and west areas. (3) The driving factors, such as the development level of the grain economy, the amount of fertilizer used per unit area, and gross domestic product (GDP) per capita, have a restraining effect on the improvement of the TFPG, in which the amount of fertilizer used per unit area is the critical factor. (4) The scale of per capita labor operation, the proportion of the grain-growing population, and output of grain per hectare exert a promoting effect on the TFPG, in which both the proportion of the grain-growing population and output of grain per hectare are the critical factors. Finally, improving the efficiency of fertilizer use, expanding the production scale of the grain planting industry, and increasing the output of grain per hectare are proposed to improve the TFGP in the Yangtze River Delta.

**Keywords:** total factor productivity; grain; spatiotemporal heterogeneity; DEA-based Malmquist index; geographically and temporally weighted regression; Yangtze River Delta area



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## 1. Introduction

Grain security has become one of the topics of great concern worldwide [1,2]. With population growth and the advancement of urbanization, the demand for grain continues to increase. At the same time, environmental issues, such as climate change, water scarcity, and land desertification, also affect agricultural production [3,4]. Ensuring grain security has become an extremely important task globally. *The World Food Security and Nutrition Situation 2022,* a report published by the Food and Agriculture Organization of the United Nations (FAO) shows that the number of people affected by hunger globally reached 828 million in 2021. The latest evidence presented in the report indicates that the world is further deviating from the target and cannot guarantee the elimination of hunger, grain insecurity, and all forms of malnutrition by 2030. Therefore, improving grain production efficiency and ensuring a sufficient grain supply in the context of the continuous progression of climate change and urbanization are the key to achieving the 2030 Agenda for Sustainable Development. This research, therefore, focuses on the grain productivity in an urbanized area in China, the Yangtze River Delta, aiming to explore the spatiotemporal characteristics and driving factors.

The Yangtze River Delta is located in the lower reaches of the Yangtze River, encompassing Shanghai and the provinces of Jiangsu, Zhejiang, and Anhui, with a total of 41 cities and an area of 358,000 square kilometers (Figure 1). In 2020, the gross domestic product (GDP) of the Yangtze River Delta region was Chinese Yuan (CNY) 24.5 trillion, with an urbanization level of over 60%. It is one of the most dynamic, open, and innovative regions in China's economic development. It occupies an important strategic position in the national modernization construction and comprehensive opening-up process, generating nearly one-quarter of the country's total economic output and one-third of the total import and export value in less than 4% of the national land area. Improving the level of the total factor productivity of grain (TFPG) and promoting comprehensive and sustainable development in the Yangtze River Delta region are of great significance for enhancing the region's innovation capacity and competitiveness, economic cohesion, regional connectivity, and policy coordination, and for enhancing national grain security. This study selects the Yangtze River Delta as the research area for two reasons. On one hand, the Yangtze River Delta region has abundant agricultural resources. Its arable land area is relatively large, with excellent soil quality and few medium-to-low-yield fields. The climate is warm, and water resources are sufficient, making it suitable for planting various crops. And the population density in the region is relatively high, and there is a high demand for agricultural products. On the other hand, the Yangtze River Delta region is one of the most developed regions in China, with high achievements and application levels of agricultural modernization, such as agricultural mechanization and the standardization of the planting industry. These have a significant impact on grain production efficiency.

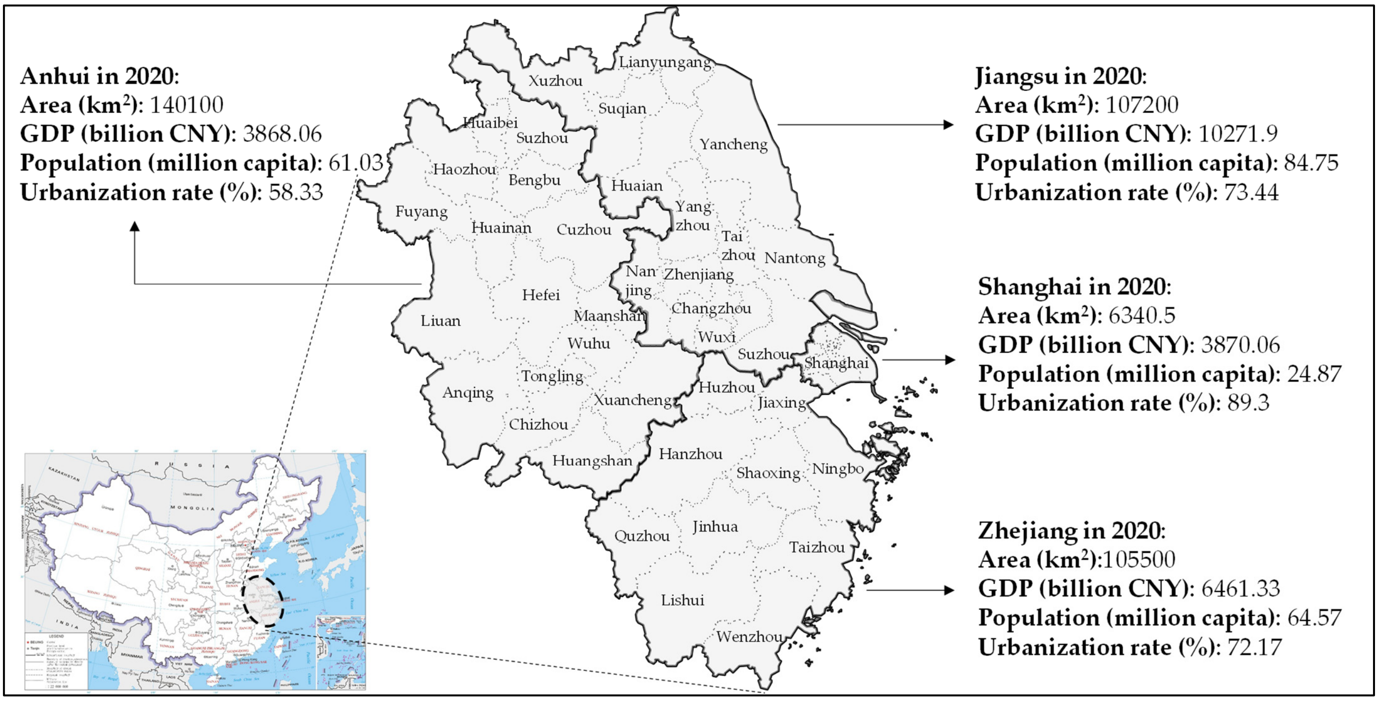


**Figure 1.** Study area of the Yangtze River Delta.

Therefore, this study aims to measure the TFPG and explore the spatiotemporal evolution characteristics of the TFPG in China's YRD region. This paper is structured as follows. A literature review was conducted and is presented in Section 2, highlighting gaps in recent research. Then, the research design is introduced in the methodology section (Section 3), together with selected indicators, the driving mechanism of spatiotemporal evolution, data sources, and methods. In our empirical analysis, the Yangtze River Delta datasets are used to explore temporal and spatial evolution characteristics of the TFPG.

The results are presented in Section 4, followed by the conclusions and future directions in Section 5.

## 2. Literature Review

Total factor productivity (TFP) refers to the comprehensive productivity of the production unit (mainly the enterprise) as a factor in a system, which is different from factor productivity (such as technical productivity). It is a productivity indicator that measures the total output per unit of total input, i.e., the ratio of the total output to the sum of all production inputs [5,6]. Based on the concept of TFP, the TFPG refers to the development and utilization efficiency of various factors, such as labor, capital, and technology, in the process of grain production, which can comprehensively reflect the development level of labor conditions, resource allocation, technological progress, and other factors [7]. And increasing the TFPG is a critical way to ensure grain security and ecological security and to achieve rural revitalization [8]. There are a lot of studies on the TFPG, including its decomposition, measurement, and critical role to GDP. For example, Yao, S. et al. (2001) used panel data of China's 30 provincial units from 1987 to 1992 to study the spatial differences in China's grain production efficiency, and they analyzed the impact of the decomposition of the TFP on low technical efficiency in detail [9]. In the research of Yang, L. (2013), the agricultural TFP of the main grain production area in China from 2002 to 2011 was recalculated by using the approach of the Malmquist–Luenberger productivity index (ML index), and comparisons of the results obtained using the conventional Malmquist index (M index) and the ML index were made in this paper [10]. Brugnaro, R. and Bacha, C.'s research focused on agricultural TFP as one of the most important agricultural variables contributing to US GDP [11]. And Chatrath, R. et al. (2007) proposed remedial measures to increase TFP in the context of the declining TFP of high-yield rice and wheat planting systems in the Indo–Ganges Plain [12].

To measure the TFPG, data envelopment analysis (DEA) and stochastic frontier analysis (SFA) are mostly employed. Bayarsaihan, T. and Coelli, T.J. (2003) used the methods of SFA and DEA to measure the variations in the TFP of grain and potatoes during 1977–1990 in Mongolia [13]. James, O. (2007) also used a combination of the methods parametric SFA and non-parametric DEA to measure the rice production capacity and technical efficiency of 19 professional grain farm producers in eastern Norway based on sample data from 1987 to 1997. Studies have shown that technological efficiency is an important factor in improving grain production capacity [14]. Furthermore, Hossain et al. (2012) used a stochastic frontier production model and DEA to estimate the growth rate of the TFP of rice crops in Bangladesh [15]. These methods usually assume that all producers follow the same technical constraints when evaluating production efficiency, but, in reality, there are differences in the technical level and resource allocation of different farmers, which cannot fully meet this ideal situation. Wei, S. et al. (2016) used the traditional three-stage Malmquist productivity index (MPI) and the bootstrap Malmquist productivity index (bootstrap MPI) to measure TFP, compensating for the shortcomings of the traditional MPI models that underestimate the technical change index and technical efficiency change index of crop production machinery components in China [16]. Zhang, Q. et al. (2018) focused on the main grain-producing areas in China, using the three-stage DEA model and the Tobit regression model to analyze the influencing factors (e.g., chemical fertilizer) on China's grain production efficiency, with the provincial panel data from 2006 to 2016 [17]. Thuzar, L. et al. (2019) focused on the regional scale, using descriptive statistics and DEA to analyze the profitability and efficiency of rice production in the Irrawaddy region of Myanmar, with the original data of 130 randomly sampled farmers [18]. Other parts of the literature used the geographically weighted regression model, but the data used in the geographically weighted regression model are cross-sectional. Due to excessive parameters, the model parameters cannot be estimated [19,20]. The spatiotemporal geographically weighted regression model can solve the above non-estimated problems through introducing the time dimension into the geographically weighted regression model [21]. Therefore, this study used the DEA–Malmquist index method to measure the TFPG and explored the spatiotemporal evolution of the TFPG with the geographically and temporally weighted regression model.

The evolution characteristics of the TFPG are important local knowledge to deepen our understanding of the TFPG at the macro scale. Panel datasets at a household, county, province, and country level are mostly employed to map the TFPG. For example, Yao, S. and Li, H. (2010) collected household data to calculate TFP using the Malmquist index method, and analyzed the evolution characteristics of the TFP from 1998 to 2004 [22]. Hou, L. et al. (2012), mainly based on county-level data, used random frontier and mapping analysis methods to explore the spatial and temporal changes in the TFP in China's agricultural production from 1995 to 1999 [23]. Song, W. et al. (2016) used the panel data of 31 provincial units in China from 1999 to 2008 to measure the changes in the TFP of crop production in China. Key, N. (2019) estimated the TFP of five scale levels of grain production farms in the Corn Belt region of the United States to determine whether the observed productivity differences are likely to persist [24]. Zhang, D. et al. (2021) explored the evolution characteristics and regional distribution differences in the TFPG of 13 major grain-producing regions of China from 2001 to 2007; they analyzed it from the perspective of the decomposition index and found that its changes mainly depend on changes in technological efficiency [25]. Zheng, Z. et al. (2022) analyzed the changes in the TFP of grain and major grain crops as commodities using provincial and time-series data merged from 1980 to 2018 in China [26]. Zhang, D. et al. (2021) and Zheng, Z. et al.'s (2022) work is the basis of this study, but both of them ignored the importance of urbanized areas. This study focuses on one of China's urbanized areas, the Yangtze River Delta, to explore its spatial and temporal heterogeneity.

The influencing factors of the TFPG are the basis to propose practical strategies. The TFPG can be affected by numerous factors, including social, economic, and natural factors, and technological progress has been widely acknowledged as a key factor. For example, Myyra, S. et al. (2009) highlighted the nature of grain cultivation in Finland while also considering the overall trend of the TFP and the challenges and influencing factors faced due to annual changes [27]. Li, L. et al. (2010) used a DEA to determine the changes in the TFP, the sources of growth, and the determinants at the farm level, and found that land terraces and access to credit greatly contributed to the TFP and technological growth [28]. Kunimitsu, Y. and Kudo, R. (2015) evaluated the impact of extreme rainfall incidence on the TFP of rice in Japan by estimating causal functions [28]. Elasraag, Y.H. and Alarcon, S. (2017) mainly focused on measuring the TFP of major wheat-producing provinces in Egypt from 1990 to 2012, and decomposed it into technological change, efficiency change, and scale change. They found that the contribution of technological change components is more important than that of efficiency change components [29]. Njuki, E. et al. (2018) focused on quantifying and investigating the role of changing weather patterns in explaining annual fluctuations in the TFPG [30]. Key, N. (2019) concluded that there was a strong positive correlation between farm size and TFP, indicating that the integration of production contributes to the recent total productivity growth of the crop sector [31]. Sheng, Y. and Chancellor, W. (2019) used farm-level data from the Australian grain industry from 1989 to 2004 to investigate the relationship between farm size, TFP, and its potential determinants [32]. Zuo, YX. (2019) analyzed the impact of agricultural human capital, product market development, factor market development, financial support, non-agricultural employment, total employment, and disaster rate on agricultural TFP [33]. Although these studies were conducted globally, they provide an important factor list for the TFPG for this study. The influencing factors on the TFPG mainly include the level of disaster caused by grain crops, the development level of grain economy, the amount of fertilizer used per unit area, the total power of agricultural machinery, per capita GDP, per capita operating scale, the proportion of the grain-growing population, and the yield per unit area of grain.

## 3. Methodology

### *3.1. Conceptual Framework of the Driving Mechanism of Spatiotemporal Evolution*

Based on the logical framework of identifying, analyzing, and solving problems (Figure 2), this study uses data from 41 cities in the Yangtze River Delta of China from 2012 to 2020 as samples. The DEA Malmquist index and geographically and temporally weighted regression are used to conduct research on three aspects: the measurement of the TFPG, spatiotemporal evolution characteristics, and a driving factor analysis. Based on the analysis of the driving factors and mechanisms, the factors influencing the improvement of the TFPG are clarified, and targeted, scientific, reasonable, and feasible policy recommendations and plans are proposed, making this research highly grounded and practical. The formation of spatiotemporal heterogeneity in the TFPG in the Yangtze River Delta region is a constantly developing and complex process, and is influenced by multiple driving factors. This study analyzed the influence coefficients of the driving factors using the GTWR model, and found that the driving factor that significantly inhibits the TFPG is the amount of fertilizer used per unit area. The driving factors that have a significant promoting effect on it mainly include the proportion of the grain-growing population and output of grain per hectare, while the development level of grain economy, per capita GDP, and per capita operating scale have a relatively low impact on the TFPG [34].

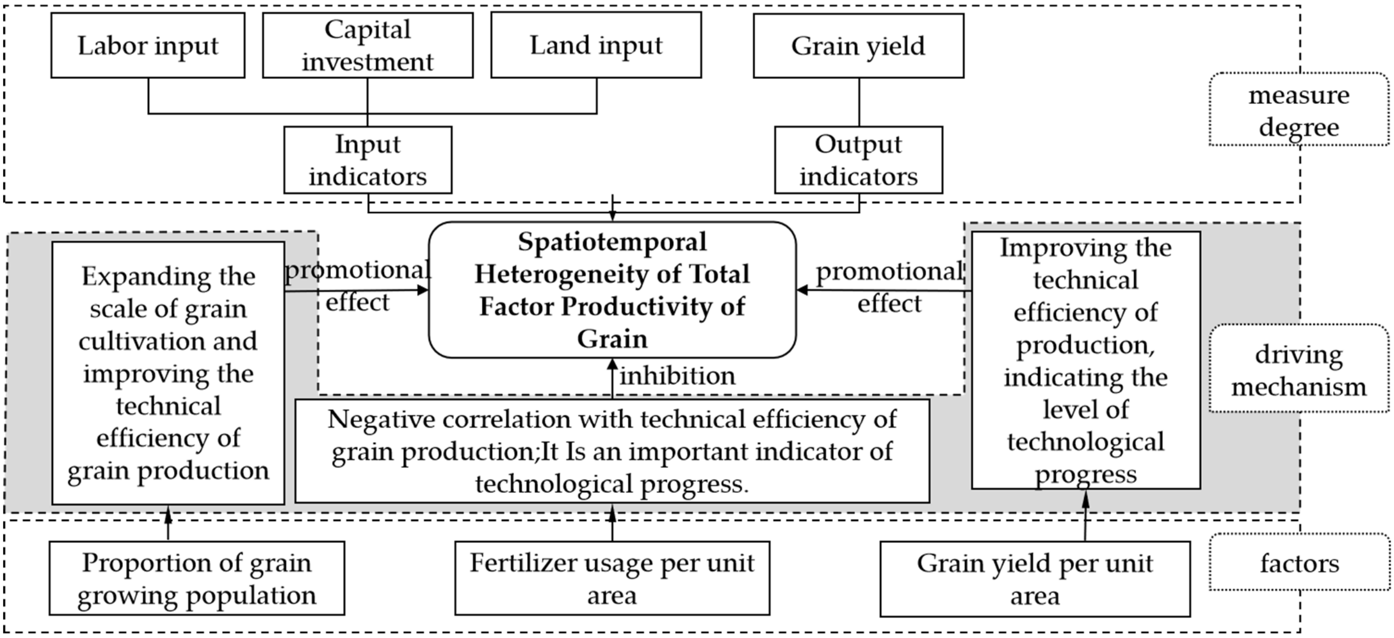


**Figure 2.** Conceptual framework of spatiotemporal evolution of total factor productivity of grain (TFPG).

Firstly, from the perspective of the inhibitory factors on the TFPG, the use of fertilizer per unit area has a strong inhibitory effect. The greater the use of fertilizer per unit area, the lower the technical efficiency and the slower the technological progress, which is not conducive to the improvement of the TFPG. Secondly, from the perspective of the promoting factors on the TFPG, the proportion of the grain-growing population and output of grain per hectare play strong and weak promoting roles, respectively. The higher the proportion of the grain-growing population, the larger the scale of grain cultivation in the region, which is beneficial for improving the TFPG. The level of output of grain per hectare is also an important indicator for measuring the technical efficiency of grain cultivation in the region, and, therefore, it has a certain promoting effect on the TFPG.

### *3.2. Indicator Setting*

#### 3.2.1. Evaluation Index System for TFPG

This study used the data envelopment analysis program (DEAP software 2.1) to calculate the TFPG in 41 cities in the Yangtze River Delta and analyzed the spatiotemporal evolution of the TFP across the Yangtze River Delta. The output indicator is the grain production of the 41 cities, and the input indicators include the number of employees in the primary industry, the sown area of grain, the total power of agricultural machinery, and the use of agricultural fertilizers (as shown in Table 1).

**Table 1.** Evaluation index system of total factor productivity of grain (TFPG).

| Indicator Type | Classification | Indicator Name | Specification | Unit |
|---|---|---|---|---|
| Output indicators | Grain yield | Grain yield | The total amount of grain produced by agricultural producers and operators within a calendar year | 10,000 tons |
| Input indicators | Labor input | Number of employees in the primary industry | The number of employees engaged in agriculture, forestry, animal husbandry, and fisheries | 10,000 people |
| | Land input | Grain sown area | The planting or transplanting area of grain crops that agricultural producers and operators should harvest on (cultivated or non-cultivated land) within the calendar year | 10,000 hectares |
| | Capital investment | Total power of agricultural machinery | The total power of various power machinery used in agriculture, forestry, animal husbandry, and fisheries | 10,000 kilowatt |
| | | Amount of agricultural fertilizer used (net amount) | The actual amount of fertilizers used in agricultural production in a given year, including nitrogen, phosphorus, total potassium, and compound fertilizers | 10,000 tons |

#### 3.2.2. Driving Factor Indicators for Factor Productivity of Grain

Based on this and existing research, this article considers data availability, accuracy, and completeness, and selects the six variables detailed below as the driving factors for analyzing the spatiotemporal heterogeneity of the TFPG (as shown in Table 2).

**Table 2.** Driving factor index system of total factor productivity of grain (TFPG).

| Indicator Name | Variable | Indicator Description | Unit |
|---|---|---|---|
| Development level of grain economy | X1 | The ratio of total agricultural output value to total agricultural, forestry, animal husbandry, and fishery output value multiplied by the sown area of grain crops/sown area of crops | % |
| Fertilizer usage per unit area | X2 | The total amount of fertilizer used divided by the sown area of crops in the area | Tons/hectare |
| GDP per capita | X3 | Total GDP divided by the total population of the same period | CNY |
| Average labor operation scale | X4 | The area sown for grain divided by the number of labor force sown for grain, where the number of labor force sown for grain is expressed by multiplying the number of agricultural employees by the area sown for grain/the area sown for crops | Hectare per person |
| Proportion of grain-growing population | X5 | Grain-sowing area divided by crop-sowing area | % |
| Output of grain per hectare | X6 | Grain yield divided by grain-sown area | Tons/hectare |

*3.3. Data Sources*

This study selected 41 cities in the Yangtze River Delta as the basic research unit, and based on the indicator system required for calculating the TFPG, the data mainly came from the "China Statistical Yearbook" and "China Rural Statistical Yearbook". The panel data from 2011 to 2020 were mainly used to measure the TFPG.

*3.4. Study Methods*

3.4.1. DEA Malmquist Index

The Malmquist index is a non-parametric model method for calculating and decomposing the growth rate of TFP. It is defined by the input–output distance function proposed by R. W. Shephard, Gaves, Christensen, and Diewert (1982), who also introduced the Malmquist index into the field of productivity analysis and proposed the concept of the Malmquist productivity index for the first time. In 1992, after further development, a non-parametric linear programming algorithm of this theory was produced so that the Malmquist productivity index could be used to establish the technical description form of multi-output and multi-input [35].

In terms of the measurement of the TFPG, the commonly used methods are the Solow residual method, the random production function and growth operation algorithm, and the DEA Malmquist index. Compared with the Solow residual method and the random production and growth function algorithm, the DEA Malmquist index has significant advantages. Firstly, compared with the parametric type, the non-parametric type does not need the shape of the production function, thus avoiding bias in the estimation of the production function model. Secondly, the DEA Malmquist index does not require factor price data, only input and output data. Thirdly, the DEA Malmquist index can also decompose the change in TFP into the change in technical efficiency and the change in technological progress. Under the assumption of variable returns to scale, the change in technical efficiency can also be decomposed into the change in pure technical efficiency and the change in scale efficiency, which can provide a more complete dynamic analysis [36–38]. Therefore, in this study we chose the non-parametric DEA Malmquist index to measure the TFPG. The specific calculation formula is as follows:

$$\begin{aligned}
&M^{t,t+1}(x^t, y^t, x^{t+1}, y^{t+1}) \\
&= \left(\frac{d^t(x^{t+1}, y^{t+1})}{d^t(x^t, y^t)} \times \frac{d^{t+1}(x^{t+1}, y^{t+1})}{d^{t+1}(x^t, y^t)}\right)^{1/2} \\
&= \frac{d^{t+1}(x^{t+1}, y^{t+1})}{d^t(x^t, y^t)} \times \left(\frac{d^t(x^{t+1}, y^{t+1})}{d^{t+1}(x^{t+1}, y^{t+1})} \times \frac{d^t(x^t, y^t)}{d^{t+1}(x^t, y^t)}\right) \\
&= tch(x^t, y^t, x^{t+1}, y^{t+1}) \times ech(x^t, y^t, x^{t+1}, y^{t+1})
\end{aligned} \tag{1}$$

whereby $tch$ represents technological progress, measuring the movement of each decision-making unit from $t$ time to $t+1$ time in the direction of production technology increasing output, $tch > 1$ indicating that technological progress occurs from $t$ time to $t+1$ time, and vice versa; $ech$ representing technical efficiency, it measures the degree of convergence of the production frontier of each decision-making unit from $t$ time to $t+1$ time. $ech > 1$ indicates that technical efficiency is improved, it will, in contrast, decline, which is based on the assumption that the returns to scale are constant. Under the assumption of variable returns to scale, technical efficiency can be further decomposed into pure technical efficiency and scale efficiency, and the formula is as follows [39]:

$$\begin{aligned}
&M^{t,t+1}(x^t, y^t, x^{t+1}, y^{t+1}) \\
&= \frac{d^{t+1}(x^{t+1}, y^{t+1}, C)/d^{t+1}(x^{t+1}, y^{t+1}, V)}{d^t(x^t, y^t, C)/d^t(x^t, y^t, V)} \times \frac{d^{t+1}(x^{t+1}, y^{t+1}, V)}{d^t(x^t, y^t, V)} \times \left(\frac{d^t(x^{t+1}, y^{t+1})}{d^{t+1}(x^{t+1}, y^{t+1})} \times \frac{d^t(x^t, y^t)}{d^{t+1}(x^t, y^t)}\right)^{1/2} \\
&= pech \times \sec h \times tch
\end{aligned} \tag{2}$$

in which $C$ means that the returns to scale are unchanged; $V$ means that the returns to scale are variable; $pech$ represents pure technical efficiency; and $\sec h$ represents scale efficiency.

When $M^{t,t+1} > 1(< 1)$, it represents the growth (decrease) of TFP from $t$ time to $t + 1$ time, and when $M^{t,t+1}$ is equal to 1 it indicates that TFP remains unchanged [40].

### 3.4.2. Geographically and Temporally Weighted Regression Model

Geographically and Temporally Weighted Regression (GTWR) is an extension of the geographically weighted regression model in the time dimension [41]. It takes into account the temporal non-stationary elements on the basis of considering the spatial heterogeneity of the influencing factors [42,43]. Its core is to add the time factor to the geographically weighted regression model for operation. The GTWR model requires the analysis object to have different spatial coordinates in different practical stages, and more overlapping coordinates will make the model results close to a linear regression analysis based on the time dimension [42].

This study uses the GTWR model based on panel data to explore the spatial and temporal heterogeneity of the driving factors of the TFPG, and constructs the following model:

$$Y_i = \beta_0(u_i, v_i, t_i) + \sum_{k=1}^{p} \beta_k(u_i, v_i, t_i) X_{ik} + \varepsilon_i; i = 1, 2, \cdots, n \quad (3)$$

where $Y_i$ is the value of the dependent variable of the $i$-thsample; $n$ is the number of samples; $k$ is the number of explanatory variables of sample $i$; $t_i$ is the time coordinate of city $i$; $\beta_0(u_i, v_i, t_i)$ represents the spatiotemporal intercept term of the sample $i$; $X_{ik}$ represents the value of the $k$-th explanatory variable value of sample $i$; $\beta_k(u_i, v_i, t_i)$ represents the regression coefficient of the $k$-th explanatory variable of sample $i$, which is a function of spatiotemporal coordinates; and $\varepsilon_i$ is the error term. All analyses were carried out using ArcGIS 10.2.

## 4. Results

### *4.1. Time Evolution Characteristics of Total Factor Productivity of Grain (TFPG)*

Overall, the TFPG in the Yangtze River Delta region showed a fluctuating trend from 2012 to 2020, with the fastest increase in TFP occurring in 2013, an increase of 12.2% compared to the previous year, followed by an increase of 9.8% in 2017. The largest decline occurred in 2016, with a decrease of 11.7%, followed by a decrease of 8.6% in 2020.

From the decomposition of the TFPG, technological progress also showed a fluctuating trend from 2012 to 2020. Among these years, technological progress was the fastest in 2019, with an increase of 13.2%; in 2015 it increased by 10.8%; and in 2016 it decreased the most, by 18.7%. During this period, the overall technological efficiency showed a downward trend, with only 2013 and 2016 showing some improvement, while the remaining years continued to decline. Among them, 2015 saw the largest decline, with a decrease of 4.4%. In addition, from the decomposition of technical efficiency, pure technical efficiency and scale efficiency fluctuated significantly over the past nine years.

From 2012 to 2020, the fluctuations in the TFPG and technological progress were relatively frequent, with relatively large fluctuations. The trend of changes in both was basically consistent, while the changes in technological efficiency, pure technological efficiency, and scale efficiency were relatively stable. This indicates that the growth and changes in the TFPG in the Yangtze River Delta region mainly relied on technological progress as the main driving force between 2012 and 2020, as shown in Figure 3 [44].

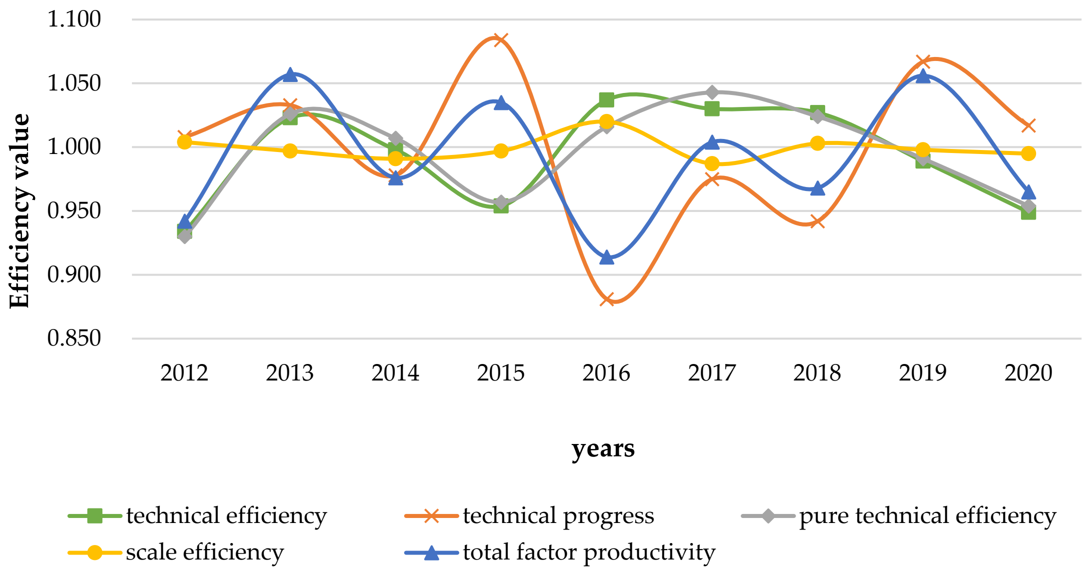


**Figure 3.** Temporal evolution of total factor productivity of grain (TFPG) in the Yangtze River Delta from 2012 to 2020. Data source: China Statistical Yearbook and China Rural Statistical Yearbook.

### *4.2. Spatial Evolution Characteristics of TFPG*

During the period from 2012 to 2020, except for in Zhenjiang City, where there was no significant annual change in the TFPG, there was an annual change in the TFPG in Ningbo City, Jiaxing City, Wuxi City, Suzhou City, Nantong City, Lianyungang City, Huai'an City, Yancheng City, Yangzhou City, Taizhou City, Suqian City, Hefei City, Bengbu City, Huaibei City, Tongling City, Chuzhou City, Fuyang City, Suzhou City, Lu'an City, and Bozhou City. Overall, the TFPG in 21 cities, including in Xuancheng City, increased, with Huaibei City experiencing the fastest increase, with an average annual increase of 3.9%. The TFPG in the other 19 prefecture-level cities decreased, with Xuzhou city experiencing the most significant decline, with an average annual decrease of 21.9%.

From the decomposition of the TFP, Jiaxing City experienced the fastest technological progress from 2012 to 2020, with an average annual increase of 2.3%, followed by Huai'an City, with an average annual increase of 2.0%. Shanghai had the fastest technological decline, with an average annual decline of 5.8%, followed by Jinhua City, with an average annual decline of 5.3%. During this period, the technological efficiency of Huaibei City increased the fastest, with an average annual increase of 3.1%, followed by Suzhou City, with an average annual increase of 2.3%. Xuzhou City experienced the fastest decline in technological efficiency, with an average annual decline of 22.5%. Further decomposing technical efficiency, Huaibei City saw the fastest increase in pure technical efficiency, with an average annual increase of 3.1%. Xuzhou experienced the fastest decline in pure technological efficiency, with an average annual decrease of 20.8%. Moreover, there was no change in pure technological efficiency in Shanghai, Hangzhou, Wenzhou, Huzhou, Zhoushan, Wuxi, Suzhou, Yancheng, Yangzhou, Zhenjiang, Taizhou, Tongling, Lu'an, or Bozhou. Bozhou City experienced the fastest increase in scale efficiency, with an average annual increase of 1.3%; Mount Huangshan City experienced the fastest decline, with an average annual decline of 2.4%, as shown in Table 3.

This study selected the TFPG from 2012 to 2020 and conducted a spatial econometric visualization analysis to examine its spatial distribution. The results show that in 2012 and 2013 the TFPG in the eastern cities in the Yangtze River Delta region was greater than 1.0, indicating an increase in the TFPG. In 2014, 2015, and 2017, the prefecture-level cities with a TFPG greater than 1.0 were mostly concentrated in the northern region of the Yangtze River Delta. In 2016, the TFPG in most prefecture-level cities in the Yangtze River Delta region was below 1.0, indicating a general decline in the TFPG in the region. It is worth noting that in 2019, except for Shanghai, Mount Huangshan, Lishui, Quzhou, and Wenzhou, where the total grain factor was less than 1.0, the other cities all had a value greater than 1.0, showing an increase. In 2018 and 2020, the spatial distribution of the TFPG in the region was not concentrated, showing decentralized spatial distribution features, as shown in Figure 4.


**Figure 4.** Spatial evolution of total factor productivity of grain (TFPG) in the Yangtze River Delta from 2012 to 2020. Data source: China Statistical Yearbook and China Rural Statistical Yearbook.

**Table 3.** Change and decomposition of total factor productivity of grain (TFPG) in cities in the Yangtze River Delta from 2012 to 2020. Data source: China Statistical Yearbook and China Rural Statistical Yearbook.

| Order Number | Area | Technical Efficiency | Technical Progress | Pure Technical Efficiency | Scale Efficiency | Total Factor Productivity |
|---|---|---|---|---|---|---|
| 1 | Shanghai | 1.000 | 0.942 | 1.000 | 1.000 | 0.942 |
| 2 | Hangzhou | 0.999 | 0.957 | 1.000 | 1.000 | 0.957 |
| 3 | Ningbo | 1.015 | 0.991 | 1.013 | 1.002 | 1.006 |
| 4 | Wenzhou | 0.981 | 0.974 | 0.980 | 1.001 | 0.955 |
| 5 | Jiaxing | 1.000 | 1.023 | 1.000 | 1.000 | 1.023 |
| 6 | Huzhou | 1.000 | 0.993 | 1.000 | 1.000 | 0.993 |
| 7 | Shaoxing | 1.007 | 0.986 | 1.007 | 1.000 | 0.993 |
| 8 | Jinhua | 0.989 | 0.947 | 0.990 | 0.999 | 0.937 |
| 9 | Quzhou | 0.999 | 0.981 | 0.998 | 1.001 | 0.980 |
| 10 | Zhousan | 1.008 | 0.961 | 1.000 | 1.008 | 0.969 |
| 11 | Taizhou | 1.013 | 0.950 | 1.013 | 1.000 | 0.962 |
| 12 | Lishui | 0.978 | 0.971 | 0.975 | 1.002 | 0.949 |
| 13 | Nanjing | 0.989 | 1.010 | 0.991 | 0.998 | 0.998 |
| 14 | Wuxi | 0.999 | 1.006 | 1.000 | 0.999 | 1.005 |
| 15 | Xuzhou | 0.775 | 1.008 | 0.792 | 0.979 | 0.781 |
| 16 | Changzhou | 0.993 | 1.003 | 0.998 | 0.995 | 0.997 |
| 17 | Suzhou | 0.999 | 1.003 | 1.000 | 0.999 | 1.003 |
| 18 | Nantong | 1.002 | 1.008 | 1.008 | 0.994 | 1.010 |
| 19 | Lianyungang | 0.999 | 1.010 | 1.001 | 0.998 | 1.008 |
| 20 | Huaian | 1.001 | 1.020 | 0.998 | 1.002 | 1.021 |
| 21 | Yancheng | 1.003 | 0.999 | 1.000 | 1.003 | 1.002 |
| 22 | Yangzhou | 1.000 | 1.018 | 1.000 | 1.000 | 1.018 |
| 23 | Zhenjiang | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 |
| 24 | Taizhou | 1.000 | 1.009 | 1.000 | 1.000 | 1.009 |
| 25 | Suqian | 1.002 | 1.008 | 1.004 | 0.998 | 1.010 |
| 26 | Hefei | 0.997 | 1.012 | 0.997 | 1.000 | 1.010 |
| 27 | Wuhu | 0.979 | 1.009 | 0.979 | 1.000 | 0.988 |
| 28 | Bengbu | 0.991 | 1.010 | 0.992 | 1.000 | 1.001 |
| 29 | Huainan | 0.984 | 1.008 | 0.977 | 1.008 | 0.993 |
| 30 | Maanshan | 0.987 | 1.009 | 1.001 | 0.986 | 0.996 |
| 31 | Huaibei | 1.031 | 1.008 | 1.031 | 0.999 | 1.039 |
| 32 | Tongling | 1.007 | 1.009 | 1.000 | 1.007 | 1.016 |
| 33 | Anqing | 0.987 | 1.002 | 0.988 | 0.999 | 0.990 |
| 34 | Huangshan | 0.992 | 1.006 | 1.016 | 0.976 | 0.998 |
| 35 | Chuzhou | 1.007 | 1.010 | 1.004 | 1.003 | 1.017 |
| 36 | Fuyang | 1.006 | 0.996 | 0.994 | 1.012 | 1.002 |
| 37 | Suzhou | 1.023 | 0.996 | 1.026 | 0.997 | 1.019 |
| 38 | Liuan | 1.009 | 0.996 | 1.000 | 1.009 | 1.006 |
| 39 | Bozhou | 1.013 | 1.001 | 1.000 | 1.013 | 1.015 |
| 40 | Chizhou | 0.983 | 1.007 | 1.001 | 0.981 | 0.989 |
| 41 | Xuancheng | 0.994 | 1.008 | 0.996 | 0.999 | 1.002 |
| 42 | Average value | 0.993 | 1.008 | 0.996 | 0.999 | 0.989 |

### *4.3. Possible Policy Recommendations*

For the improvement of the TFPG in the Yangtze River Delta region, the use of chemical fertilizers per unit area, the proportion of the grain-growing population, and the yield of grain per unit area are important driving factors. Therefore, policy recommendations for improving the TFPG should be highly targeted. Firstly, efforts should be made to promote advanced fertilization techniques and high-quality fertilizers, improve the efficiency of fertilizer use, and reduce the use of chemical fertilizers per unit area. These efforts are beneficial for improving production efficiency and reducing input costs, and also for increasing grain yield and increasing grain output [45]. Secondly, it is necessary to expand the production scale of the grain planting industry based on the actual situation of each region, promote the scale production of grain, and leverage the advantages of the scale effect. Thirdly, the increase in the output of grain per hectare should be taken as an important starting point and area of focus, and measures such as improving soil fertility, selecting suitable high-yield varieties of grain crops for production, and using advanced scientific planting techniques and methods should be used to improve the production efficiency of grain planting, thus improving the output of grain per hectare. In short, it is necessary to implement more scientific and targeted measures to improve the TFPG, improve the production efficiency of grain, safeguard national grain security, and promote high-quality agricultural development by reducing the impact of inhibitory factors and increasing the impact of promoting factors. This will also provide a constructive exploration for China's formulation of the Three Rural Policies [46,47].

## 5. Discussion

In order to conduct a quantitative analysis of the driving factors of the changes in the TFPG in the Yangtze River Delta region, this study selected the panel data of 41 cities in the Yangtze River Delta region from 2012 to 2020, for a total of 2583 data samples; used the GTWR model to explore the impact of the driving factors on the TFPG; and judged the importance of their impacts on the TFPG through the sizes of their impact coefficients. The greater the absolute value of the influence coefficients of each driving factor, the greater their impact on the TFPG. Before the regression analysis, through the multicollinearity test of the six driving factors of 41 cities in the Yangtze River Delta from 2012 to 2020, the VIFs of the six driving factors of grain economic development level, fertilizer use per unit area, GDP per capita, the scale of operation per labor, the proportion of the grain-growing population, and grain output per unit area were found to be 8.962, 3.767, 2.782, 4.539, 2.968, and 1.365, respectively. The VIFs of the six indicators were less than 10, indicating that there is no multicollinearity among the six driving factors. The regression results of the GTWR model are shown in Table 4. From the analysis of the global regression results, it was found that the goodness of fit ($R^2$) was 0.794, the sum of squares of residuals (RSS) was 56831.400, and the Akaike information criterion (AIC) was 54203.800. In addition, all coefficients of the GTWR model were significant overall ($p < 0.05$). The above regression results indicate that the GTWR model can be used to evaluate the relationship between the TFPG and the six driving factors (see Table 4).

**Table 4.** Regression results of GTWR model. Data source: China Statistical Yearbook and China Rural Statistical Yearbook.

| Evaluating Indicator | Numerical Value |
|---|---|
| Goodness of fit (R2) | 0.794 |
| Correction (R2) | 0.792 |
| Akaike information criterion (AIC) | 54,203.800 |
| Residual sum of squares (RSS) | 56,831.400 |

### 5.1. *Temporal Heterogeneity of Driving Factors*

In order to further analyze the temporal heterogeneity of the impact coefficients of the driving factors affecting the TFPG, we analyzed the mean of the impact coefficients of each driving factor on the TFPG from 2012 to 2020. According to the influence coefficients of each driving factor, it can be seen that the influence coefficients of three driving factors, namely the development level of grain economy, the amount of fertilizer used per unit area, and the per capita GDP, are negative. This indicates that these three factors have inhibitory effects on the improvement of the TFPG. Among them, the absolute value of the influence coefficient of fertilizer used per unit area is larger, and the inhibitory effect is greater. The other three driving factors, namely, the scale of per capita labor operation, the proportion of the grain-growing population, and the output of grain per hectare, have a positive impact coefficient, indicating that they have a promoting effect on the TFPG. Among them, the absolute value of the impact coefficient of the proportion of the grain-growing population is relatively large, meaning it has a significant promoting effect and impact on the TFPG.

According to the impact coefficient of the grain economic development level, the inhibitory effect of the grain economic development level on the TFP decreased year by year from 2012 to 2019, and the inhibitory effect improved in 2020. According to the coefficient of the influence of fertilizer usage per unit area, the inhibitory effect of fertilizer usage per unit area on the TFPG increased year by year from 2012 to 2018, and the inhibitory effect weakened in 2019 and 2020. The per capita GDP impact coefficient decreased year by year from 2012 to 2020, indicating that the inhibitory effect of the regional economic development level on the TFPG increased year by year. The impact coefficient of per capita operating scale, after a slight decrease from 2012 to 2013, shows a yearly increasing trend, indicating that the promoting effect of per capita operating scale on the improvement of the TFPG increased year by year. From the impact coefficient of the proportion of the grain-growing population, the overall trend shows an upward trend from 2012 to 2019, indicating that the promoting effect of the proportion of the grain-growing population on the TFPG increased year by year, but it weakened in 2020. From the perspective of the impact coefficient of output of grain per hectare, before 2015 both the impact coefficient and the promoting effect increased year by year. However, after 2015 the impact coefficient of output of grain per hectare began to decline, and the promoting effect of output of grain per hectare on the TFPG weakened year by year, as shown in Figure 5.

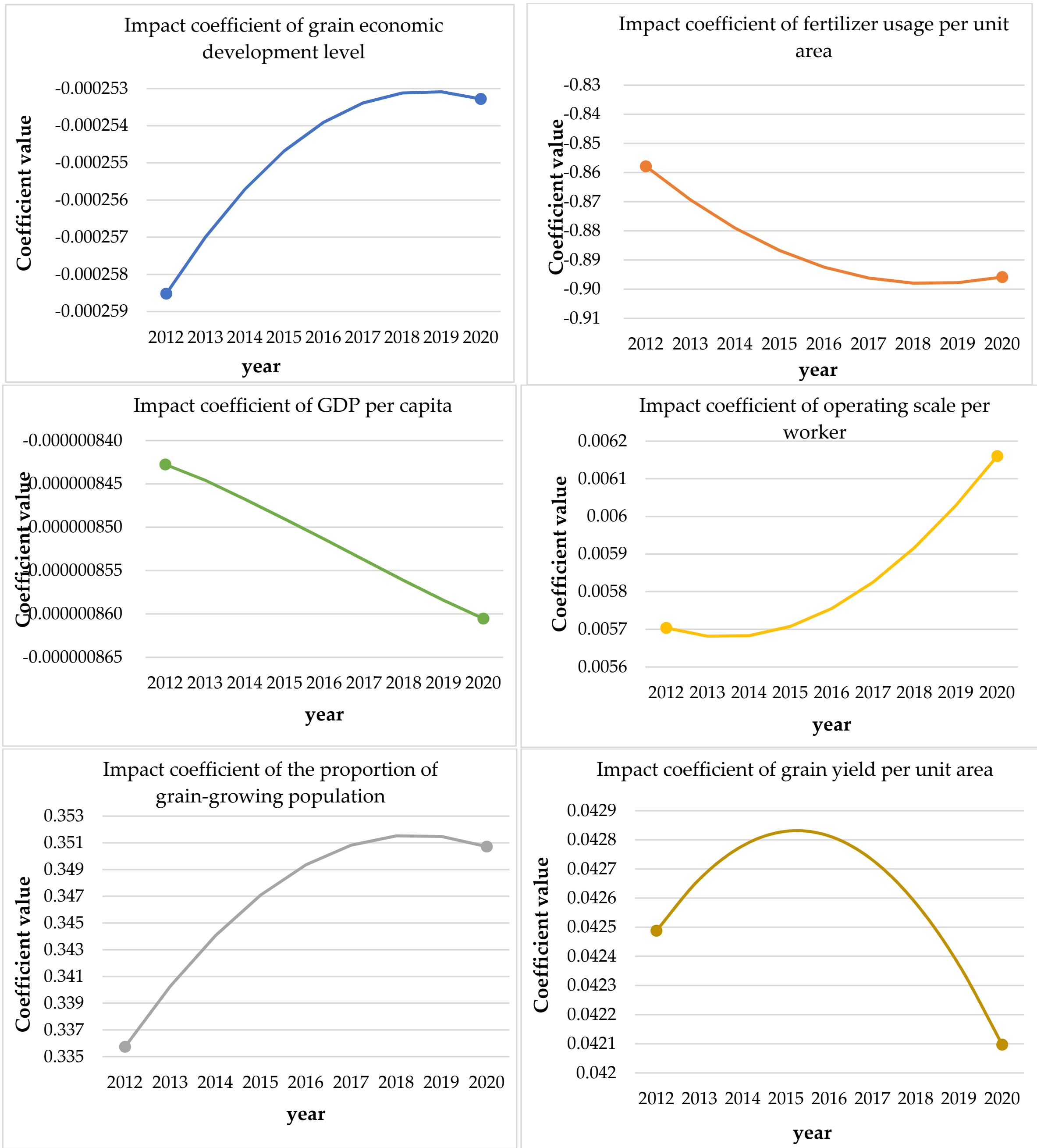


**Figure 5.** Time heterogeneity of driving factors of total factor productivity of grain (TFPG). Data source: China Statistical Yearbook and China Rural Statistical Yearbook.

### *5.2. Spatial Heterogeneity of Driving Factors*

The GTWR model was used to obtain the impact coefficient of the TFPG in the cities in the Yangtze River Delta from 2012 to 2020 and the spatial heterogeneity of the impact coefficient of each driving factor from 2012 to 2020. Among them, the use of fertilizer per unit area (X2), the scale of per capita operation (X4), the proportion of the grain-growing population, (X5), and the grain output per unit area (X6) were the main driving factors affecting the TFPG.

The spatial heterogeneity of the impact coefficient of per capita GDP in the Yangtze River Delta is not obvious; the spatial distribution of the impact coefficient of the grain economic development level shows the characteristics of being high in the east and low in the west, and the distribution of the low and high values of the impact coefficient is relatively concentrated. From the perspective of spatial distribution, the development level of grain economy in the eastern Yangtze River Delta has a relatively small inhibitory effect on the TFPG. The impact coefficients of fertilizer usage per unit area and per capita labor management scale show a spatial distribution pattern of high in the southeast and low in the northwest, indicating that the inhibitory effect of fertilizer usage per unit area in the southeast of the Yangtze River Delta is smaller than that in the northwest, while the promoting effect of per capita labor management scale on the TFPG is greater in the southeast than in the northwest. The impact coefficient of the proportion of the grain-growing population and the impact coefficient of grain output per unit area show the spatial heterogeneity characteristics of low in the southeast and high in the northwest. This indicates that the promoting effect of both on the TFPG is the increasing spatial distribution from southeast to northwest, as shown in Figure 6 [8,48].

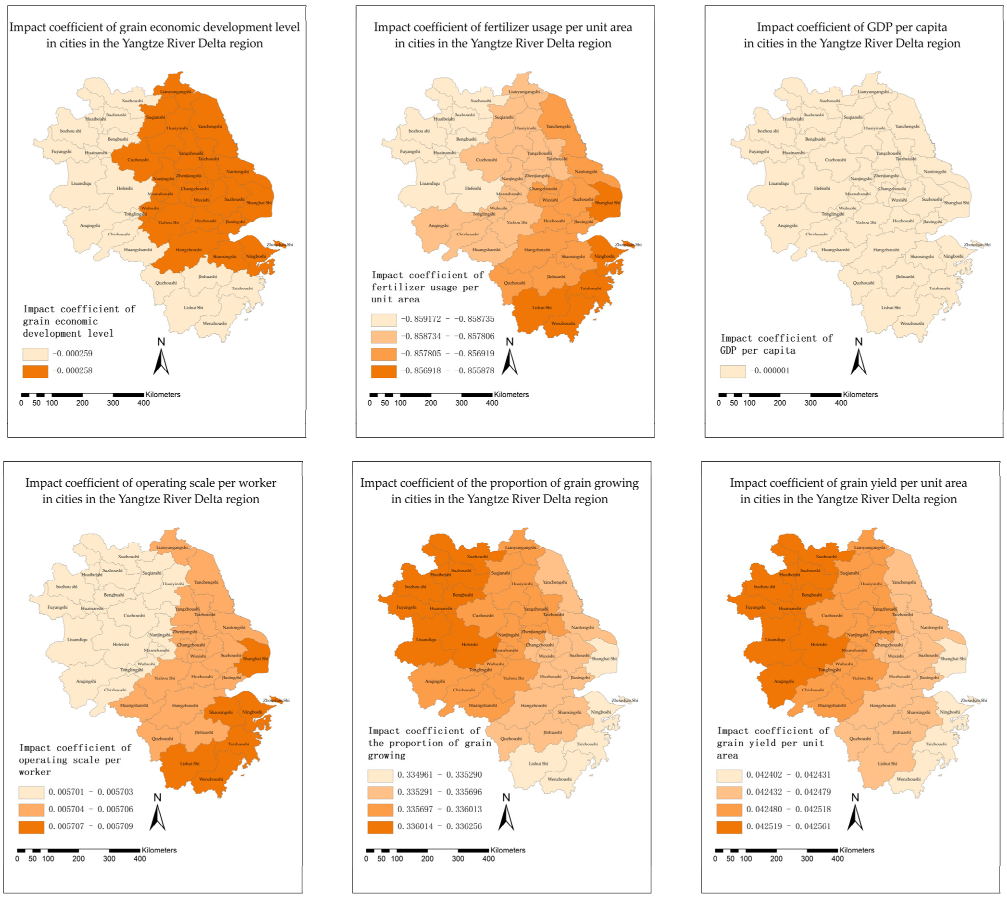


**Figure 6.** Spatial heterogeneity of driving factors of total factor productivity of grain (TFPG). Data source: China Statistical Yearbook and China Rural Statistical Yearbook.

## 6. Conclusions

By using the DEA Malmquist index and a geographically and temporally weighted regression model, the TFPG in various cities in the Yangtze River Delta from 2012 to 2020 was measured. Based on the measurement results, the spatiotemporal evolution characteristics of the TFPG were analyzed, and the spatiotemporal heterogeneity of the influencing coefficients of the driving factors was analyzed and studied. The following conclusions were drawn:

The first conclusion concerns the temporal evolution characteristics of the TFPG in various cities in the Yangtze River Delta. Overall, the TFPG in the Yangtze River Delta region showed a fluctuating trend from 2012 to 2020, with the fastest increase in the TFPG occurring in 2013 and the largest decrease occurring in 2016. From 2012 to 2020, the fluctuations in the TFPG and technological progress were relatively frequent, with relatively large fluctuations. The trend of changes in both was basically consistent, while the changes in technological efficiency, pure technological efficiency, and scale efficiency were relatively stable. This indicates that the growth and changes in the TFPG in the Yangtze River Delta region mainly relied on the monorail drive of technological progress between 2012 and 2020.

The second conclusion concerns the spatial evolution characteristics of the TFPG in various cities in the Yangtze River Delta. During the period from 2012 to 2020, the distribution of the TFPG in various cities in the Yangtze River Delta was relatively scattered, showing a spatial distribution pattern of high in the north and low in the south and a spatial distribution pattern of high in the east and low in the west. Among them, the annual TFPG in Zhenjiang City did not change significantly, while the TFPG in 21 prefecture-level cities, namely, Ningbo, Jiaxing, Wuxi, Suzhou, Nantong, Lianyungang, Huai'an, Yancheng, Yangzhou, Taizhou, Suqian, Hefei, Bengbu, Huaibei, Tongling, Chuzhou, Fuyang, Suzhou, Lu'an, Bozhou, and Xuancheng, increased overall. Huaibei City experienced the fastest increase, with an average annual increase of 3.9%. The TFPG in the other 19 prefecture-level cities decreased annually, with Xuzhou city experiencing the most significant decline, with an average annual decrease of 21.9%.

The third conclusion concerns the analysis of the driving factors of the TFPG. This study constructed a driving factor indicator system, which includes six variables. By using the GTWR model to analyze the impact coefficients of the driving factors, it was found that, among the six driving factors, the use of fertilizer per unit area had a strong inhibitory effect on the TFPG; the proportion of the grain-growing population and output of grain per hectare had a promoting effect on the TFPG; and the three driving factors of the development level of grain economy, per capita GDP, and average labor operation scale had a relatively low impact on the TFPG.

This study still has some shortcomings. Firstly, in terms of measuring the TFPG, this study used the DEA Malmquist model for measurement. However, there are still many measurement methods besides this model, and whether this method is the most scientific requires further verification. There is also room for further improvement in the selection of input and output indicators. Secondly, in terms of selecting driving factors, the driving factors for total grain productivity in this study were mainly selected based on existing research. On the one hand, not all driving factors have differential impact coefficients and need to be screened. On the other hand, the selection of driving factors also results in problems, such as being uncomprehensive, unscientific, and biased. Therefore, based on the analysis and summary of the research shortcomings mentioned above, future research will focus on comparing various methods for calculating the TFPG, improving the input and output indicators, comprehensively and scientifically selecting driving factors, and conducting in-depth analyses in order to improve the current research and make up for its shortcomings.

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