German Journal of Agricultural Economics Vol. 73 (2024), No. 2, 1-25
Original Research Article
https://doi.org/10.52825/gjae.v73i2.1351

Submitted: 22 Aug. 2022 | Accepted: 04 Apr. 2024 | Published: 31 May 2024

Agricultural Green Total Factor Productivity in Shandong Province of China

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Abstract: Sustainable development of agriculture has an important impact on both society and economy. In order to understand the patterns of spatio-temporal variation and the factors influencing agricultural green total factor productivity (AGTFP), this paper used Shandong province of China as a case study. Utilizing the SBM-DEA and Malmquist models, along with panel regression methods, the study analyzes AGTFP based on data from the Shandong Statistical Yearbook (2009-2019). The results showed that: (1) the AGTFP in Shandong province was smaller than the total factor productivity when not considering the undesirable output, and the AGTFP in most regions of Shandong province needed to be improved. (2) The AGTFP of Shandong province showed an annual rising trend, especially in the eastern and northern regions. (3) In addition to the levels of technology and management, the industrialization and level of personal development of farmers is also shown to have impacted on AGTFP. Recommendations include adopting advanced technologies, enhancing land management, promoting tertiary sector development, expanding agricultural processing, and improving farmer skills through education and training to boost AGTFP to achieve a sustainable agricultural economy.

Keywords: AGTFP, SBM-DEA Model, Malmquist Model, Center of Gravity Model, Coefficient of Variation, Panel Regression

1 Introduction

Since the reform and opening up in 1978, China's rural economy had developed rapidly, and the output of various agricultural products had increased significantly. In recent years, the output of major agricultural products such as grain, oil, vegetables, fruits, meat, poultry and eggs were among the highest in the world (Rmlt, 2019; Chinairn, 2020).

Shandong province is located in the east coast of China, with its excellent geographical location (see Appendix A), suitable climatic conditions and a developed agricultural economy. It was often ranked as the first in China in terms of gross output value of agriculture, added value of agriculture, export value among other indicators (Song et al., 2012). Shandong was also ranked as the third in grain crop yield and sown area of vegetables, the first in total fruit production, and the first in total output value of animal husbandry (China Statistical Yearbook, 2009-2019). Agricultural development requires the use of a large amount of chemical fertilizers, and such use in Shandong province has long been the second highest in China, second only to Henan province (China Statistical Yearbook, 2009-2019). Grain, vegetable, and other crops produce massive amount of straw and livestock breeding produces a great deal waste.

Excessive use of chemical fertilizer, waste from livestock breeding and inappropriate disposal of straw cause serious non-point source pollution in rural area. Agricultural non-point source pollution is the pollution generated in agricultural production activities that pollutants enter water through farmland surface runoff, soil flow, farmland drainage and underground leakage (Ma et al., 2009).

It is estimated that agricultural non-point source pollution accounts for one-third of the total water pollution in China (Li, 2022). Among them, CODcr, TN, and TP accounted for 44%, 57% and 67%, respectively, of the total discharge of each pollutant (Huang et al., 2012). CODcr is the chemical oxygen consumption measured by using potassium dichromate ($K_2Cr_2O_7$) as oxidant, namely the dichromate index. TN (Total Nitrogen) is the total amount of nitrogen present in soil or water. It is calculated as the milligrams of nitrogen per liter of water. TN is commonly used to indicate the degree of nutrient pollution in water bodies. The higher the TN value, the more severe the water quality pollution. TP (Total Phosphorus) is the total content of phosphorus in soil or water. It is one of the indicators used to measure the level of water pollution. A higher TP value indicates a higher degree of water quality pollution.

Therefore, it is necessary to study issues related to agricultural sustainable development, especially the green agricultural productivity. This is because improving green agricultural efficiency can reduce inputs of agricultural production resources and the generation of pollutants, thereby promoting agricultural sustainability. Considering that the agricultural development of Shandong province plays a very important role in China, it has great significance to study the patterns of spatio-temporal variation and mechanism associated with AGTFP in Shandong province. Studying AGTFP in the temporal dimension allows us to understand its patterns of change over time, while studying it in the spatial dimension enables us to understand its spatial distribution characteristics.

We first calculated agricultural non-point source pollutants and used them as the undesirable output. We selected variables such as agricultural GDP, agricultural labor force, the total power of agricultural machinery, arable land area, and irrigated land area for the calculation of AGTFP in Shandong province. Then, the spatiotemporal variation patterns of AGTFP in Shandong province were analyzed based on the calculated results. Finally, panel data analysis was conducted to explore the mechanisms of changes in AGTFP.

The rest of the paper is organized as follows: Section 2 is primarily a literature review that aims to enhance readers' understanding of diverse perspectives on agricultural total factor productivity (agricultural TFP) and AGTFP. Section 3 outlines the selection of indicators and data characteristics. Section 4 describes the calculation methods. Section 5 analyzes the calculation results. Section 6 discusses the implications and significance of the findings. Finally Section 7 encompasses the conclusion and recommendations.

2 Literature Review

Agricultural growth decomposes growth into total input use and total factor productivity (TFP). In particular, TFP has become the primary source of agricultural growth worldwide (USDA, 2012). To a large extent, agricultural modernization is the process in which TFP's contribution to agricultural economic growth is expected to continue rising. Since agricultural TFP is of great significance to agricultural development, many scholars have studied the trends and factors of agricultural TFP from different perspectives:

(1) Studies at Different Spatial Scales

Some scholars have examined agricultural TFP at various spatial scales, including global, continental, and national levels. For instance, Fuglie (2015) conducted an analysis of global agricultural TFP for the years 1961-2012. The results suggested that the rate of agricultural TFP growth had accelerated in recent decades. Alhassan (2021) conducted a study using data from 38 countries in sub-Saharan Africa (SSA) to investigate the impact of agricultural TFP on environmental degradation. The findings revealed a U-shaped relationship between agricultural TFP and carbon dioxide emissions in SSA.

(2) Studies from Perspectives of Different Influencing Factors

Many scholars have studied the effects of different influencing factors on agricultural TFP. For instance: Li et al. (2021) investigated the relationship between China's rapid urbanization and agricultural TFP. The results revealed a U-shaped relationship between urbanization and agricultural TFP. Through a study of agricultural TFP in 15 countries in South Asia and Southeast Asia, Liu et al. (2020) discovered that human capital had a positive influence on the growth of agricultural TFP. Espoir et al. (2021) in their study of agricultural TFP in Africa. They highlighted that good governance can play a pivotal role in enhancing agricultural productivity. Yang et al. (2019) found rural human capital positively contributes to the local agricultural TFP, while adjustments in crop structure significantly restrain the increase in local agricultural TFP levels.

In the process of agricultural development, the extensive use of chemical fertilizers and pesticides can lead to environmental pollution. Additionally, the large amounts of manure generated by livestock and poultry breeding also contribute to environmental degradation. The discrepancy between TFP calculations that do not consider the losses caused by environmental pollution and the actual TFP can easily lead decision-makers to develop policies that are unfavorable to green development. To promote the harmonious development of agriculture and the environment, scholars have incorporated environmental pollution factors into the analysis of agricultural TFP, resulting in the concept of AGTFP (Xu et al., 2020).

A few scholars have studied AGTFP. Yang et al. (2022) discovered a significantly positive relationship between rural human capital and AGTFP in their study of AGTFP across 28 provinces (cities and autonomous regions) in China. Han et al. (2018) identified that planting structure has a slight negative effect on AGTFP in their analysis. Using panel data from 30 Chinese provinces, Wang and Xie (2022) conducted an analysis of the relationship between human capital and AGTFP. The results indicated that the significant improvement in the quality of human capital notably influences the growth of AGTFP in China. Wang and Xiao (2022) found that the massive population migration from rural to urban areas during the urbanization process results in a continuous deterioration of agricultural green productivity. Liang and Long (2015) conducted an analysis of the factors influencing the growth of AGTFP in 31 provincial-level administrative regions of China. They found that the impact of agricultural fiscal expenditures on AGTFP was not particularly significant, and the advancement of industrialization hindered the increase in AGTFP growth rate. Yang et al. (2019) examined the spatial variation of AGTFP and its driving factors and found that the impact of economic development level, agricultural structure, and financial support for agriculture on AGTFP exhibited regional variability.

Some scholars have also studied AGTFP in Shandong province. For example, Zhang and Liu (2015) used the C^2R model in DEA to evaluate the agricultural productivity in Shandong province. C^2R model is a model built on the premise of *constant return to scale*, which is applicable to the situation where the input increase in a certain proportion and the output also increase in proportion to the input. However, agricultural production did not fit this situation. Jiao (2013) analyzed the agricultural productivity of Shandong province. Jiao (2013) mainly adopted industrial pollutant discharges to represent the undesirable output of agriculture. However, this method was deficient as industrial pollutants often had no connection with agricultural production.

In order to better understand the pattern and determinants of AGTFP in Shandong province, we employed the Slacks-Based Measure (SBM)-DEA method and other approaches to calculate and analyze AGTFP. This paper considered agricultural non-point source pollutants as the undesirable output and conducted statistical analysis of AGTFP in Shandong province. We treated the undesirable output as an input to make a dynamic comparison of AGTFP.

3 Index Selection and Data Description

3.1 Index Selection of AGTFP

DEA is a research method for multi-factor input and output evaluation. When performing calculations, it necessitates the selection of input and output variables. This approach combines input and output variable data from readily available statistical sources. Output variables were agricultural Gross Domestic Product (GDP) and agricultural non-point source pollutants in each city. Input variables were agricultural labor population, the total power of agricultural machinery, cultivated land area, irrigated land area and chemical fertilizer consumption.

(1) Agricultural GDP: The value of agricultural economic output is expressed by the added value of agriculture, forestry, animal husbandry and fishery in units of 10,000 Yuan (CNY). To eliminate the impact of inflation, the output values were converted into constant price in 2008 based on the GDP deflator in different years and different local cities and municipalities.
(2) Pollutant: The calculated agricultural non-point source pollutants were used, with the unit being ton.
(3) Agricultural labor population: Agricultural labor refers to the number of individuals engaged in agricultural industry, the unit was ten thousand.
(4) The total power of agricultural machinery: the unit is kilowatt. Agricultural machinery refers to equipment such as tractors, harvesters, and planters that are used in agricultural production. Hong et al. (2022) utilized this indicator in their study on the impact of digital inclusive finance and optimization of agricultural industry structure on AGTFP.
(5) Cultivated land area: Agricultural production required the occupation of land, we chose cultivated land area as the input, with the unit being hectare.
(6) Irrigated land area: Due to the lack of irrigation water data, the actual area of irrigation land was used instead, and the unit was 1,000 hectares.
(7) Chemical fertilizer consumption: A mass of chemical fertilizer was used in agricultural production. We used the fertilizer after converted to pure volume, and the unit was ton.

3.2 Factor Selection in Panel Regression

We selected influencing factors in a panel regression model by considering the interplay among various factors affecting AGTFP, while also taking into account data availability and factors employed in previous research studies.

The independent factors in the model include urbanization (Fang et al., 2021), agricultural industrial structure (Liu et al., 2021; Liu, 2018), industrialization (Fang et al., 2021), the influence of government on agriculture (Liu et al., 2021; Yang et al., 2022), farmers' characteristics (Ye et al., 2023), economic development level (Wang and Wang, 2017) and distance from port (Li et al., 2022). The explanations of each factor are as follows:

(1) Urbanization ratio: In the process of urbanization, part of the rural population was transferred to cities because of education, work, medical care and other reasons, which led to serious aging in rural areas and the abandonment of land. This would directly affect the output of agriculture.
(2) Agricultural industrial structure: It was represented by the proportion of grain crop area to total crop sown area, which indicated adjustment of agricultural structure. Because the benefits produced by food crops and cash crops are different, it would have an impact on AGTFP.

(3) Industrialization: The proportion of value-added by the secondary sector to the GDP in each city was utilized as a measure of the level of industrialization. Industrialization has the potential to attract labor migration from agriculture, with many young and middle-aged individuals entering factory employment, resulting in a shortage of labor in rural areas. This phenomenon can have a negative impact on agricultural TFP. However, the industrial sector can also contribute to the improvement of agricultural TFP by manufacturing advanced agricultural machinery for use in agricultural production.
(4) The influence of government on agriculture: We used proportion of fiscal expenditure on agriculture, forestry and water resources to the fiscal expenditure. This factor reflected the state of government support for agriculture. The more the government invested in agriculture, the more agricultural scientific research results, and the higher the agricultural technical efficiency there would be.
(5) Personal development of farmers: There was no directly related data for this indicator. We used the proportion of farmers' expenditure on education, culture and entertainment in their annual consumer expenditure.
(6) Economic development level: Per capita GDP was used instead, and the unit was ten thousand CNY.
(7) Distance from port: Qingdao port has been one of the famous ports in the world. This paper intended to measure the influence of the port on AGTFP by using the distance between each city and Qingdao. The distance from each city to Qingdao was calculated based on longitude and latitude coordinates. The distance of Qingdao to itself was calculated by using the area of Qingdao, calculating the average radius and it represented the distance of Qingdao.

3.3 Data Description

The data covers 17 cities in Shandong province, with a time span from 2008 to 2018, and each observation variable consists of 187 values. It is important to note that in China, the next level of administrative units below the provincial level is the city, which includes both urban and rural areas.

The descriptive characteristics of these data can be found in Appendix B. Due to the distribution of these data across 17 cities and spanning 11 years, there are significant differences between the variables. The main variables showing an increasing trend include agricultural GDP, per capita GDP, irrigated land area, urbanization ratio, agricultural industrial structure, the influence of government on agriculture, and personal development of farmers. The variables showing a decreasing trend include agricultural labor population, total power of agricultural machinery, cultivated land area, fertilizer usage, pollutant quantity in agriculture, and industrial structure of the secondary sector. The variable that remains unchanged is the distance of each city from the Qingdao port.

4 Methods

4.1 Calculation of Agricultural Pollutant Discharge

This paper used the unit survey evaluation method to calculate the discharges of agricultural pollutants. The pollution unit was the non-point source pollution unit, which was the smallest independent unit that produced non-point source pollution. This could be measured statistically, such as fertilizer, crop straw, livestock and poultry breeding. The coefficients involved in the calculation of pollutant discharge were mainly adopted from Liang (2009) and Lai (2003). For detailed information, please refer to the papers by Liang and Lai. Calculation method of pollutant discharge was as the following:

$$E = \sum_i EU_i \rho_{ik} (1 - \eta_i) \quad (1)$$

where *E* is the discharge of agricultural non-point source pollutants, i.e., COD_{Cr}, TN, and TP, i is pollution unit, EU_i is the number of agricultural pollution unit i , ρ_{ik} is the pollution intensity coefficient of pollutant k in agricultural pollution unit i , which is the amount of pollutants produced by a pollution unit. The pollutant indexes considered in this paper were the production of TN, TP and COD_{Cr} (Lai et al., 2004). η_i is coefficient of utilization efficiency of agricultural pollution unit i . 1-η_i is coefficient of run-off of agricultural pollution unit *i*.

Nitrogen fertilizer and phosphorus fertilizer in chemical fertilizers are important sources of TN and TP in agricultural non-point source pollution. The calculation methods for these pollutants are as follows: The consumption of fertilizer is calculated by the usage of nitrogen and phosphate fertilizers *after conversion to pure volume*. The fertilizer *after conversion to pure volume* refers to the amount of nutrients of each fertilizer summed by the mass percentage of N, P_2O_5 and K_2O. Thus, nitrogen fertilizer after conversion becomes the amount of TN; phosphorus fertilizer after conversion is the amount of P_2O_5. Therefore, the content of P in P_2O_5 is about 43.66%. The amount of TP is the product of the phosphate fertilizer *after conversion to pure volume* and 43.66%. The loss of TN, TP can then be derived by multiplying the amount of TN, TP and their loss rates respectively. The nitrogen loss rate is 20% and the phosphorus loss rate is 7% in Shandong province.

Livestock and poultry farming is another significant source of agricultural non-point source pollution. The calculation methods for the pollutants generated from livestock and poultry farming are as follows: The production of pollutants from livestock and poultry breeding = the amount of livestock and poultry kept at the end of the year × the excretion coefficient of pollutants from livestock (Table 1) and poultry breeding sources × the excretion loss rate. The excreta loss rate of livestock and poultry in Shandong province was 27.6% COD_{Cr}, 24.4% TN and 21.2% TP.

Table 1. Annual excretion coefficient of pollutants from livestock and poultry (kg/unit)

Pollution unit *i*	**CODCr**	**TN**	**TP**
cattle	401.500	61.100	10.070
swine	47.880	4.510	1.700
sheep	4.400	2.280	0.450
poultry	1.165	0.275	0.115

Source: coefficients adopted from Liang (2009) and Lai (2003)

Solid waste generated from agricultural production is also an important source of agricultural non-point source pollution. The calculation methods for this type of pollutant are as follows:

Farmland solid waste is mainly crop straw. The calculation of farmland solid waste involves the consideration of factors such as the crop straw to grain ratio, pollution production coefficient, and emission coefficient. Since there are various types of vegetables with different waste proportions, this study assumed an average solid waste proportion of 0.51 for vegetables. See Table 2, Table 3, Table 4, and Table 5 for the specific coefficients for calculation.

In the context of Shandong, taking into account the proportion of straw utilization and nutrient loss, it was found that the loss proportions for CODcr, TN, and TP were 11.57%, 10.39%, and 8.61% respectively.

Table 2. Main crop straw grain ratio

type	paddy	wheat	corn	bean	potato	Oil crops
straw: grain	0.970	1.030	1.370	1.710	0.610	2.260

Source: coefficients adopted from Liang (2009) and Lai (2003)

Table 3. Pollution production coefficient of different crop straw

unit	pollution production coefficient (10^{-3} t/t)		
	CODcr	TN	TP
paddy	5.630	5.820	0.420
wheat	6.390	5.150	0.900
corn	11.230	10.690	2.390
bean	17.610	22.230	2.240
potato	2.260	1.830	0.670
Oil crops	20.570	45.430	3.060
vegetable	5.100	0.920	0.450

Source: coefficients adopted from Liang (2009) and Lai (2003)

Table 4. Straw utilization ratio in Shandong (%)

fertilizer	fodder	fuel	raw material	incineration	stack	total
23.600	31.000	19.600	6.300	5.800	13.700	100.000

Source: coefficients adopted from Liang (2009)

Table 5. Straw utilization and nutrient loss ratio (%)

nutrient	fertilizer	fodder	fuel	raw material	incineration	stack
CODcr	20.000	0.000	0.000	0.000	0.000	50.000
N	15.000	0.000	0.000	0.000	0.000	50.000
P_2O_5	5.000	0.000	0.000	0.000	10.000	50.000

Source: coefficients adopted from Liang (2009) and Lai (2003)

4.2 Dimension Reduction of Pollutants

Due to the presence of three pollutants - CODcr, TN and TP, and that DEA analysis requires the decision-making unit to be more than twice the sum of input variables and output variables, the dimension of pollutants needed to be reduced. Here principal component analysis (PCA) method was used for dimensionality reduction. Subsequently, the coefficient from the Component Score Coefficient Matrix was used as the weight to calculate the sum of CODcr, TN and TP, and the sum was taken as the undesired output.

After the three pollutants were processed by using PCA, the contribution of variance in data by the first principal component was above 95%, so the first principal component can be used to replace the three pollutants.

With this, the formula was restructured to be:

$$FAC = a_1 * X_1 + a_2 * X_2 + a_3 * X_3 \tag{2}$$

where FAC was the pollutant after dimensionality reduction, $\mathbf{a_1}$, $\mathbf{a_2}$, $\mathbf{a_3}$ were component score coefficients and X_1, X_2 and X_3 are the three pollutants: CODcr, TN and TP.

4.3 SBM (Slacks-Based Measure)-DEA Approach

The SBM model is a type of DEA model. Compared to other DEA models, the SBM model allows for the measurement of efficiency changes under non-expected output constraints (Tan and Liu, 2022). Therefore, it can better reflect the essence of efficiency evaluation than other models (Tu and Liu, 2011).

Tone (2001) proposed and developed an SBM-DEA model. In the SBM-DEA model:

Suppose production systems have *n* decision making units, DEA analysis would be an economic system or a process (one unit), which would be considered as an entity. Within a certain possible extent, it works by putting a number of factors of production and output of a certain number of "products". Such entities (units) are called decision-making units (DMUs). Each unit contains three vectors of input: desirable output and undesirable output. They are denoted as $x \in R^m$, $y^g \in R^{s1}$, $y^b \in R^{s2}$.

Define the matrix of X, Y^g, Y^b

where

$[X] = [x1, \cdots, xn]^T \in R^{m \times n}$,

$[Y^g] = [y_1^g, \cdots, y_n^g]^T \in R^{s1 \times n}$,

$[Y^b] = [y_1^b, \cdots, y_n^b]^T \in R^{s2 \times n}$, X >0, Y^g >0, Y^b >0.

Define the production possibility set p as:

$$p = \{(x, y^g, y^b) | x \geq \lambda x, y^g \leq \lambda Y^g, y^b \leq \lambda Y^b, \lambda \geq 0\} \tag{3}$$

Then the SBM model based on variable return scale is expressed by formula (2):

$$p^* = min \frac{1 - \frac{1}{m} \sum_{i=1}^{m} \frac{s_i^-}{x_{io}}}{1 + \frac{1}{s1 + s2} \left[\sum_{i=1}^{s1} \frac{s_r^g}{y_{r0}^g} + \sum_{i=1}^{s2} \frac{s_r^b}{y_{r0}^b} \right]} \tag{4}$$

where s is the slacks of input and output, λ is weight vector, objective function p^* with respect to s^-, s^g, $s^b$is strictly decreasing and $0 \leq p^* \leq 1$. For a particular decision unit, if and only if $p^* = 1$ and s^-, s^g, s^b are 0, the comprehensive efficiency is effective. When $p^* < 1$ or s^-, s^g, $s^b$are not complete zeroes, it indicates that the decision unit is inefficient, and the technical efficiency or scale efficiency is also invalid, so there is a need to improve the input and output.

4.4 Malmquist Method

The SBM-DEA model is able to perform statistical analysis on cross-sectional data, but it does not measure the temporal trend of AGTFP, and hence cannot make a dynamic comparison. The Malmquist index can be used to solve this problem by combining cross-sectional data analysis with time series data analysis.

It can decompose this productivity change into technical change and technical efficiency change (Sathye, 2002).

Formally, the Malmquist index value of stage *t* was defined by Caves as

$$agtfp^t = \frac{D^t(x^{t+1},\ \ y^{t+1})}{D^t(x^t,\ \ y^t)} \tag{5}$$

Then, the Malmquist index value of phase *t+1* is

$$agtfp^{t+1} = \frac{D^{t+1}(x^{t+1},\ \ y^{t+1})}{D^{t+1}(x^t,\ \ y^t)} \tag{6}$$

Taking the geometric mean value of the two-phase Malmquist index values, the Malmquist index can be expressed as

$$agtfp = \left[\frac{D^t(x^{t+1},\ \ y^{t+1})}{D^t(x^t,\ \ y^t)} \times \frac{D^{t+1}(x^{t+1},\ \ y^{t+1})}{D^{t+1}(x^t,\ \ y^t)}\right]^{1/2} \tag{7}$$

If $agtfp$ >1, it indicates that the efficiency is increased when comparing with the efficiency in the previous year. When $agtfp$ <1, the efficiency becomes lower than that of the previous year. Finally, when $agtfp$ =1, it suggests that no change is found when comparing it with that of the previous year.

We can decompose the Malmquist index into

$$\begin{aligned} \mathrm{agt}fp &= \left[\frac{D^{t+1}(x^{t+1},\ \ y^{t+1})}{D^t(x^t,\ \ y^t)}\right] \times \left[\frac{D^t(x^{t+1},\ \ y^{t+1})}{D^{t+1}(x^{t+1},\ \ y^{t+1})} \times \frac{D^t(x^t,\ \ y^t))}{D^{t+1}(x^t,\ \ y^t)}\right]^{1/2} \\ &= effch \times techch \end{aligned} \tag{8}$$

where $effch$ represents changes in technical efficiency level, $techch$ is change in technology level.

4.5 Calculation of Center of Gravity

In geographical research, the shift of center of gravity (CoG) could reflect the change in spatial distribution of geographical things and phenomena. The CoG among a set of geographical locations can be simply defined as $(\overline{x_\iota}, \overline{y_\iota})$ where $\overline{x_\iota}, \overline{y_\iota}$ are the average coordinates of all i locations.

The calculation method for an attribute-weighted regional CoG is to assume that a large region was composed of several subregions, and the center coordinates of the i-th subregion is (X_i,Y_i), M_i is the certain attribute value of that subregion i so that the coordinates of the regional CoG for that attribute values is (Tellier and Vertefeuille, 1995):

$$\begin{aligned} \bar{x} &= \frac{\sum_{i=1}^{n} M_i * X_i}{\sum_{i=1}^{n} M_i} \\ \bar{y} &= \frac{\sum_{i=1}^{n} M_i * Y_i}{\sum_{i=1}^{n} M_i} \end{aligned} \tag{9}$$

When the ($\bar{x}$,$\bar{y}$) value of a spatial phenomenon is significantly different from the geometric center of the region, it indicates an uneven distribution of the spatial phenomenon, or “deviation of CoG”. The deviation direction indicates the “high value” part of the spatial phenomenon, while the deviation distance indicates the degree of equalization.

4.6 Calculation Method for Regional AGTFP Disparities

To explore the levels of changes in AGTFP over time in Shandong province, the coefficient of variation (CV) formula was used to calculate such changes. CV can measure the relative statistic of the degree of data dispersion.

The formula used for this is given as follows:

$$\sigma_t = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n}(x_{it}-\overline{x_t})^2} \tag{10}$$

where i ($i=1,2,\cdots n$) stands for different regions; t is the study time, x_{it} means the AGTFP at region i at the time of t, $\overline{x_t}$ denotes the average AGTFP of regions at time t. When value of σ decreases, the difference of AGTFP is reduced and AGTFP converges. Otherwise, AGTFP diverges, and regional differences vary significantly.

4.7 Panel Regression Model

Panel data not only expands the information of research samples, but also contains the dynamic behavior information of research objects (Hsiao, 2007). The general form of the panel data model is as follows (Bai, 2008):

$$y_{it} = \sum_{k=1}^{k}\beta_{ki}X_{kit} + u_{it} \tag{11}$$

where, $i = 1, 2, \ldots, N$, and N is the number of objects; $T = 1, 2, \ldots, t$, and T is the number of known time points. y_{it} is the observed value of the dependent variable for the object i at time t; X_{ki} denotes the value of the independent variable k for the object i at time t; β_{ki} is the parameter to be estimated while u_{it} is a random error.

There are different methods for building panel data regression models (Gao et al.,2016) among which fixed effects models and random effects models are two commonly forms. Fixed effect models or random effect models could be selected depending on the application. The Hausman test is necessary to determine which model to choose in the calculation. In general, fixed effects models are preferred when $p < 0.5$ in the Hausman test, while random effects models are chosen when $p > 0.5$ in the test.

5 Results

5.1 Static Analysis of AGTFP in Shandong Province

From Table 6, it can be observed that each year in Shandong province, there were approximately 8 or 10 cities with an index equal to 1, indicating high efficiency in AGTFP. There were also about 5 cities with indices below 0.6, indicating low efficiency. Among the 17 cities, Jinan, Dongying, Yantai, Weifang, Jining, Weihai, and Laiwu consistently maintained high efficiency in AGTFP. Qingdao, Zaozhuang, Taian, Linyi, and Dezhou showed a slight decrease in

AGTFP. On the other hand, Zibo, Rizhao, Liaocheng, Binzhou, and Heze demonstrated an increase in AGTFP.

Considering the length and tediousness of analyzing AGTFP results for all 17 cities year by year from 2008 to 2018, this paper decided to select three time points, namely 2008, 2013, and 2018, for analysis. These time points are spaced four years apart and can effectively reflect the spatial changes in AGTFP in Shandong province. Additionally, the year 2013 was chosen as a significant time node because it marked China's entry into the stage of excess production capacity of chemical fertilizer (Cnr, 2014), leading to a decline in product prices (Sannong, 2014).

Table 6. Changes in AGTFP in different cities of Shandong province

City	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
Jinan	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Qingdao	1.000	1.000	0.765	0.825	0.783	0.744	0.745	0.755	0.754	0.759	0.774
Zibo	0.582	0.571	0.595	0.633	0.613	0.622	0.617	0.630	1.000	1.000	1.000
Zaozhuang	1.000	1.000	1.000	1.000	1.000	0.792	0.723	0.669	0.743	0.714	0.713
Dongying	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.598	1.000	1.000	1.000
Yantai	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Weifang	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Jining	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Taian	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.824	0.713	0.795	0.800
Weihai	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Rizhao	0.684	0.650	0.680	0.690	0.673	0.702	0.736	1.000	1.000	0.744	0.794
Laiwu	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Linyi	0.605	0.580	0.559	0.559	0.552	0.531	0.545	0.543	0.575	0.571	0.580
Dezhou	0.378	0.382	0.379	0.372	0.365	0.357	0.353	0.353	0.276	0.364	0.373
Liaocheng	0.524	0.500	0.510	0.530	0.525	0.483	0.476	0.476	0.503	0.521	0.537
Binzhou	0.430	0.419	0.425	0.434	0.436	0.445	0.427	0.419	0.522	0.507	0.511
Heze	0.396	0.374	0.369	0.369	0.357	0.345	0.338	0.324	0.357	0.358	0.345

Source: derived from statistical data analyzed using the SBM method

In order to show the impact of undesirable output on green TFP more intuitively, this paper utilized both the SBM model that considered undesirable outputs and the SBM model that only considered GDP output to calculate respectively. The result is shown in Table 7. It can be seen from Table 7 that when undesirable output was taken into account, the TFP of almost all regions were lower than those of TFP without undesirable output in the same period.

The results showed that the AGTFP in 10 places including Jinan, Qingdao and Weihai were relatively high in 2008, with the efficiency of 1; Rizhao and Linyi were in the state of medium efficiency while Binzhou, Dezhou, Heze and other 5 places were in invalid efficiency. In 2013, the AGTFP in Jinan, Yantai, Weihai and other 8 places were relatively high, with an efficiency of 1; Qingdao, Zaozhuang and other four places were in medium efficiency. Binzhou, Linyi, Heze and other 5 places showed invalid efficiency. In 2018, the AGTFP in 8 places, including Jinan, Zibo and Dongying, were relatively high, with an efficiency of 1; Rizhao, Qingdao and other four places were in medium efficiency; Dezhou, Liaocheng, Heze and other 5 places showed invalid efficiency. Figure 1, Figure 2 and Figure 3 were created based on the AGTFP in 2008, 2013 and 2018, respectively. From the distribution of AGTFP values, it can be seen that most places in eastern Shandong had relatively high efficiency; most places in western Shandong had relatively low efficiency, and the areas in central Shandong were in the middle, where the areas with high efficiency and the areas with low efficiency coexisted. In Liang and Xi (2022), as well as in the analysis conducted by Liu and Zhang (2018) on the AGTFP in Shandong province, it was also observed that there exists such regional disparity in AGTFP.

The primary reasons for this regional disparity are closely related to variations in the agricultural machinery ownership across different regions.

Table 7. Comparison of the results of the regression models that include the undesirable outputs and not include the undesirable outputs

DMU	2008		2013		2018	
	included	Not included	included	Not included	included	Not included
Jinan	1.000	1.000	1.000	1.000	1.000	1.000
Qingdao	1.000	1.000	0.744	0.833	0.774	0.830
Zibo	0.582	0.663	0.622	0.713	1.000	1.000
Zaozhuang	1.000	1.000	0.793	0.792	0.713	0.767
Dongying	1.000	1.000	1.000	1.000	1.000	1.000
Yantai	1.000	1.000	1.000	1.000	1.000	1.000
Weifang	1.000	1.000	1.000	1.000	1.000	1.000
Jining	1.000	1.000	1.000	1.000	1.000	1.000
Taian	1.000	1.000	1.000	0.900	0.800	0.836
Weihai	1.000	1.000	1.000	1.000	1.000	1.000
Rizhao	0.684	0.762	0.702	0.815	0.794	0.882
Laiwu	1.000	1.000	1.000	1.000	1.000	1.000
Linyi	0.605	0.713	0.531	0.659	0.580	0.708
Dezhou	0.378	0.525	0.357	0.502	0.373	0.515
Liaocheng	0.524	0.623	0.483	0.594	0.537	0.634
Binzhou	0.430	0.576	0.445	0.592	0.511	0.665
Heze	0.396	0.514	0.345	0.459	0.345	0.462

Source: derived from statistical data analyzed using the SBM method

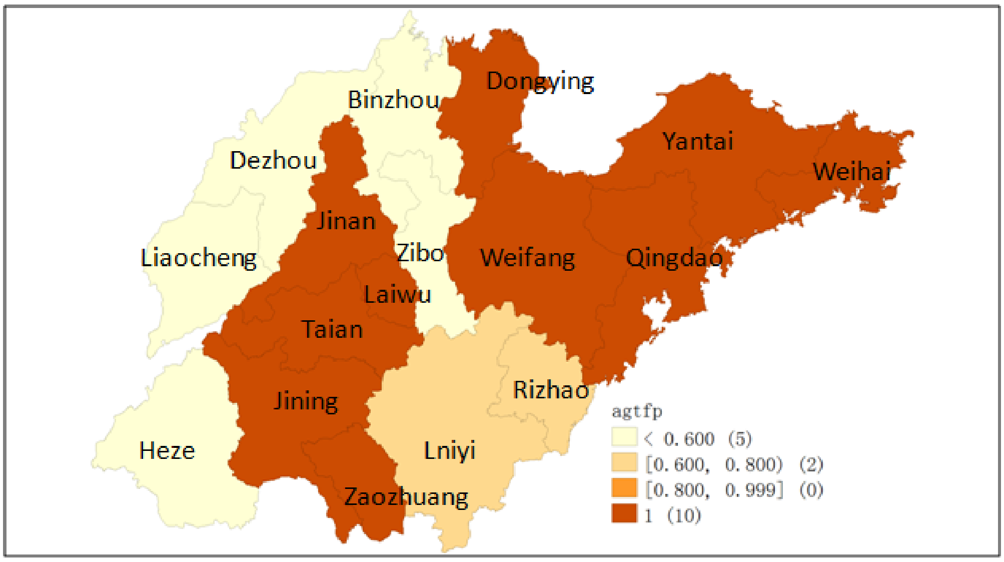

Figure 1. The distribution of AGTFP in Shandong province in 2008

Source: the graph was plotted based on the data from Table 6.

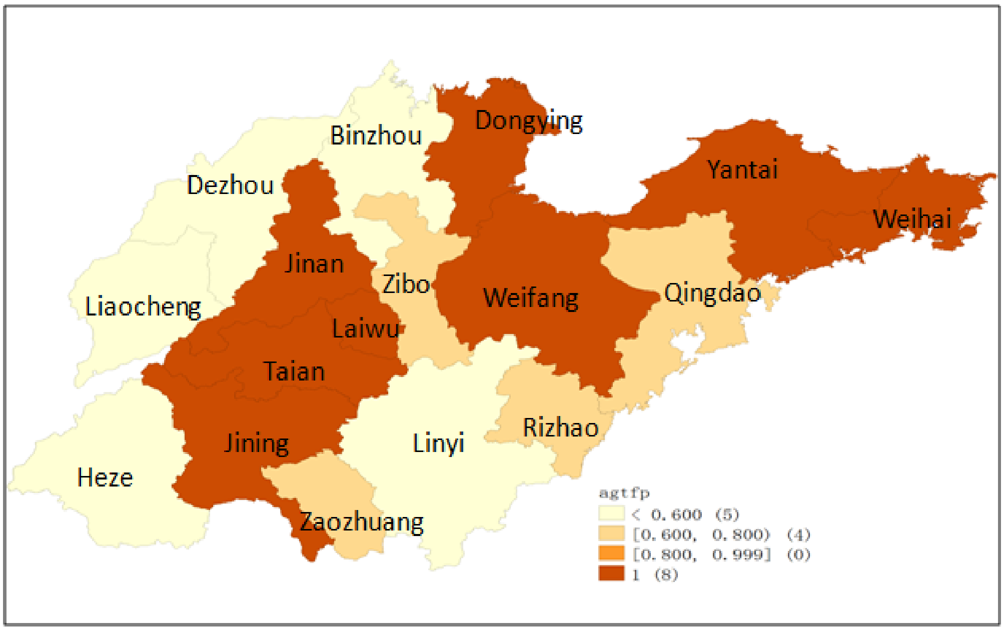

Figure 2. The distribution of AGTFP in Shandong province in 2013

Source: the graph was plotted based on the data from Table 6.

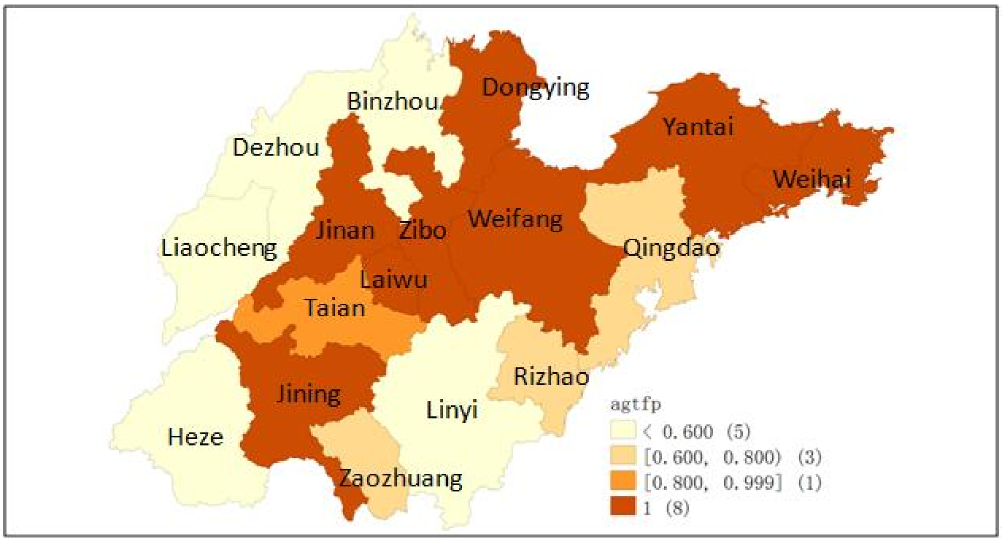

Figure 3. The distribution of AGTFP in Shandong province in 2018

Source: the graph was plotted based on the data from Table 6.

5.2 Temporal Trends of AGTFP in Shandong Province

The Malmquist index was calculated for the entire studied time period and the results are shown in Figure 4. In the last 10 years, the AGTFP in Shandong had presented a growing trend, and the growth rate had been increasing over these years. The growth rate in 2009 was 101.5% compared with that of 2008. The growth rate in 2018 was 108.5%, compared with that of 2017. The significant increase in AGTFP in 2016 was likely due to the fact that the Shandong provincial government had paid more attention to agriculture, focused on the implementation of agricultural modernization measures and reduced agricultural production costs (Li and Yu-chi, 2019). For example, enhancing the level of agricultural mechanization and implementing land transfer systems, where smaller landowners who are not inclined to engage in cultivation lease their land to larger-scale operators or businesses, can facilitate large-scale, mechanized farming, ultimately leading to an increase in TFP. Simultaneously, due to the intensification of operations, this approach can also lower production costs.

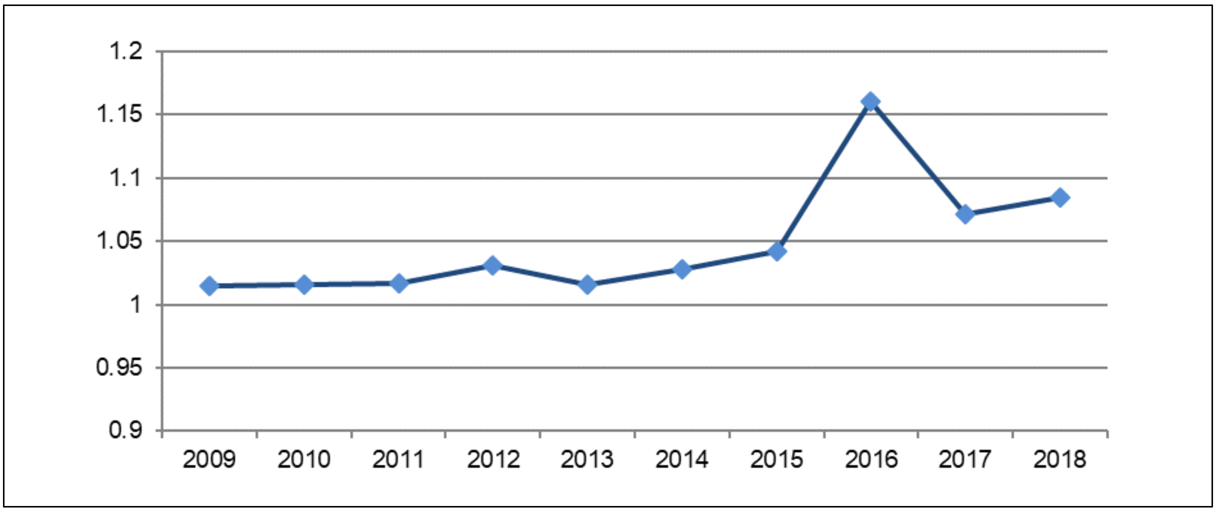

Figure 4. The yearly trend of AGTFP in Shandong province

Source: data derived from the calculated Malmquist index

5.3 Inter-City AGTFP Comparative Analysis

5.3.1 Comparative Study of Average AGTFP and its Components Across Cities

Figure 5 shows the average values of Malmquist index of AGTFP in various cities of Shandong province from 2009 to 2018. In recent 10 years, the AGTFP of all cities in Shandong had been increasing continuously, but there were obvious differences. Areas with relatively fast growth were Binzhou, Zibo, Jinan and other areas. The slower growth was found in Zaozhuang, Laiwu, Taian and other areas.

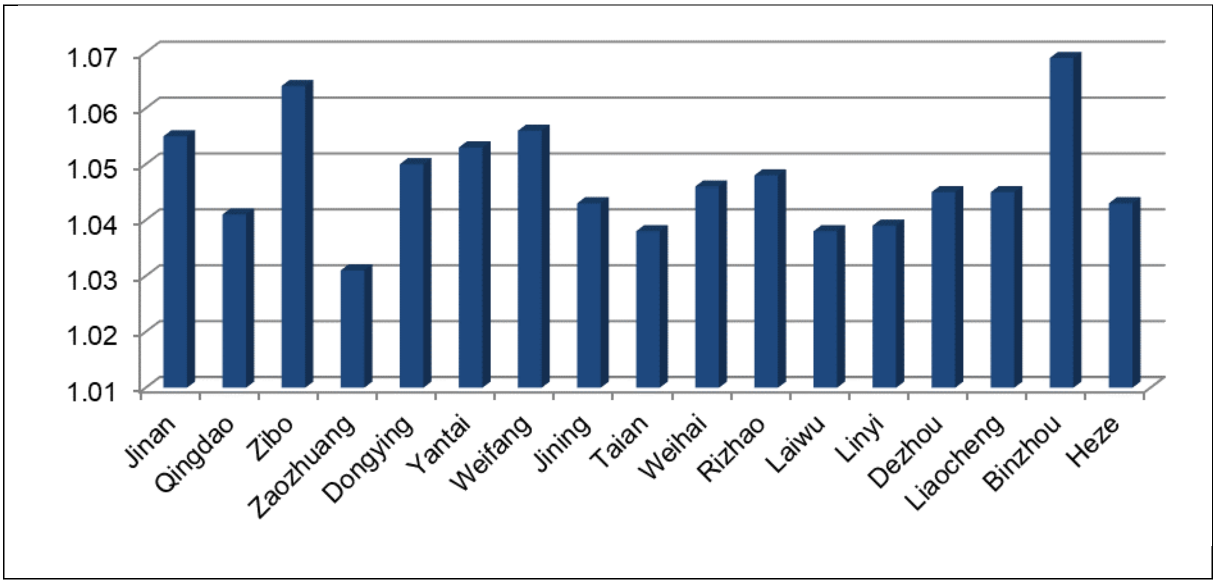

Figure 5. Average AGTFP in each city of Shandong province (2009-2018)

Source: data derived from the calculated Malmquist index

The Malmquist index can be decomposed into *effch* and *techch.* It can be seen from Table 8 that the changes in AGTFP were mainly caused by *techch*, indicating that agricultural technological progress led to the improvement of AGTFP. Agricultural technological progress includes measures such as improving agricultural machinery levels, using high-quality seeds, and implementing other technological advancements in agricultural practices. This result was consistent with the research conclusion in Sheng et al. (2020) that “It is widely believed that technological progress had played an essential role in contributing to the rapid productivity growth in China’s agricultural sector”.

effch represents the combined efficiency of agricultural management level and input factors. Jinan, Zibo, Yantai and other 7 regions had been improved, but the remaining 10 regions were not efficient. This was in line with the current situation of low overall agricultural efficiency, extensive agricultural management and large numbers of farmers unwilling to engage in agricultural production.

Table 8. Decomposition of AGTFP of cities

city	*effch*	*techch*	*agtfp*
Jinan	1.000	1.055	1.055
Qingdao	0.991	1.050	1.041
Zibo	1.015	1.048	1.064
Zaozhuang	0.988	1.044	1.031
Dongying	0.990	1.061	1.050
Yantai	1.000	1.053	1.053
Weifang	0.998	1.059	1.056
Jining	1.000	1.043	1.043
Taian	0.995	1.043	1.038
Weihai	1.000	1.046	1.046
Rizhao	1.008	1.039	1.048
Laiwu	0.993	1.045	1.038
Linyi	0.999	1.041	1.039
Dezhou	0.995	1.050	1.045
Liaocheng	0.999	1.046	1.045
Binzhou	1.010	1.058	1.069
Heze	0.988	1.056	1.043

Source: data derived from the decomposition of the Malmquist index

5.3.2 Comparison Analysis of AGTFPT Trends Across Cities

Table 9 shows the AGTFP data of all regions in Shandong province from 2009 to 2018. Table 6 presents AGTFP calculated using the SBM method, which allows for the analysis of AGTFP across different cities in the same year. On the other hand, Table 9 displays AGTFP calculated using the Malmquist Index method, providing a convenient means to analyze the temporal trends of AGTFP within the same region.

In light of the temporal shifts, it is evident that the AGTFP in every city had been experiencing a consistent and progressive increase. In terms of the change characteristics of AGTFP, three distinct types can be discerned: (1) Jinan, Zibo, Weifan, Jining, Rizhao, Liaocheng, Binzhou, and Heze were keeping relatively high growth rates，AGTFP were greater than 1 annually. (2) In Zaozhuang, Laiwu and Linyi, AGTFP gradually developed from low efficiency to high efficiency, and changed from less than 1 to higher than 1. (3) The remaining 6 cities were experiencing fluctuating growth. Although the efficiency was less than 1 in some years, the overall efficiency was also constantly improving.

Table 9. The trend of AGTFP in 17 cities of Shandong province

City	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
Jinan	1.028	1.026	1.026	1.038	1.006	1.028	1.035	1.191	1.103	1.084
Qingdao	1.014	0.996	1.036	1.027	1.032	1.041	1.034	1.140	1.036	1.061
Zibo	1.017	1.033	1.028	1.024	1.028	1.029	1.044	1.319	1.083	1.064
Zaozhuang	0.972	0.996	0.997	1.017	1.016	1.016	1.024	1.174	1.068	1.044
Dongying	1.021	1.021	1.018	1.015	0.968	1.015	0.972	1.225	1.151	1.127
Yantai	1.021	1.024	0.997	1.038	1.025	1.035	1.041	1.211	1.023	1.135
Weifang	1.007	1.012	1.014	1.045	1.027	1.040	1.050	1.204	1.073	1.108
Jining	1.021	1.013	1.022	1.038	1.027	1.043	1.044	1.104	1.067	1.053
Taian	0.999	1.011	0.997	1.015	1.012	1.008	1.015	1.143	1.141	1.050
Weihai	1.030	1.019	1.006	1.029	0.985	1.033	1.075	1.032	1.033	1.236
Rizhao	1.019	1.039	1.013	1.026	1.048	1.043	1.165	1.056	1.061	1.016
Laiwu	0.992	0.989	1.008	1.045	1.017	1.019	1.012	1.251	1.033	1.034
Linyi	0.999	0.985	1.008	1.022	1.006	1.020	1.034	1.339	1.004	1.019
Dezhou	1.038	1.029	1.023	1.050	1.010	1.038	1.051	0.864	1.243	1.143
Liaocheng	1.040	1.035	1.038	1.047	1.010	1.042	1.051	1.062	1.049	1.077
Binzhou	1.019	1.017	1.032	1.033	1.023	1.007	1.038	1.348	1.037	1.176
Heze	1.020	1.030	1.028	1.028	1.030	1.025	1.037	1.158	1.032	1.050

Source: AGTFP calculated using the Malmquist Index method

5.4 Analysis of Center of Gravity Shift in AGTFP Within Shandong Province

The latitude and longitude coordinates of each city in Shandong were obtained from the website (Jingweidu, 2020). M_i was the AGTFP calculated by using Malmquist method. The CoG model was used to calculate the CoG of AGTFP in Shandong province from 2009 to 2018, which could reflect the spatial changes in the trajectory of the CoG of AGTFP in Shandong and could reveal their spatial pattern.

The CoG is plotted in Figure 6. It can be seen from the figure that the center of gravity was 118.16°E and 36.38°N in 2009, and 118.20°E and 36.41°N in 2018. When compared with the geometric center of Shandong province (118.14°E,36.33°N) (Li, 2019), the centers were both on the east and north. This indicates that the AGTFP in eastern Shandong was higher than that in western cities, and the AGTFP in northern cities was higher than that in southern cities. In addition, the CoG generally had a tendency to shift eastward and northward, indicating that regional differences were increasing.

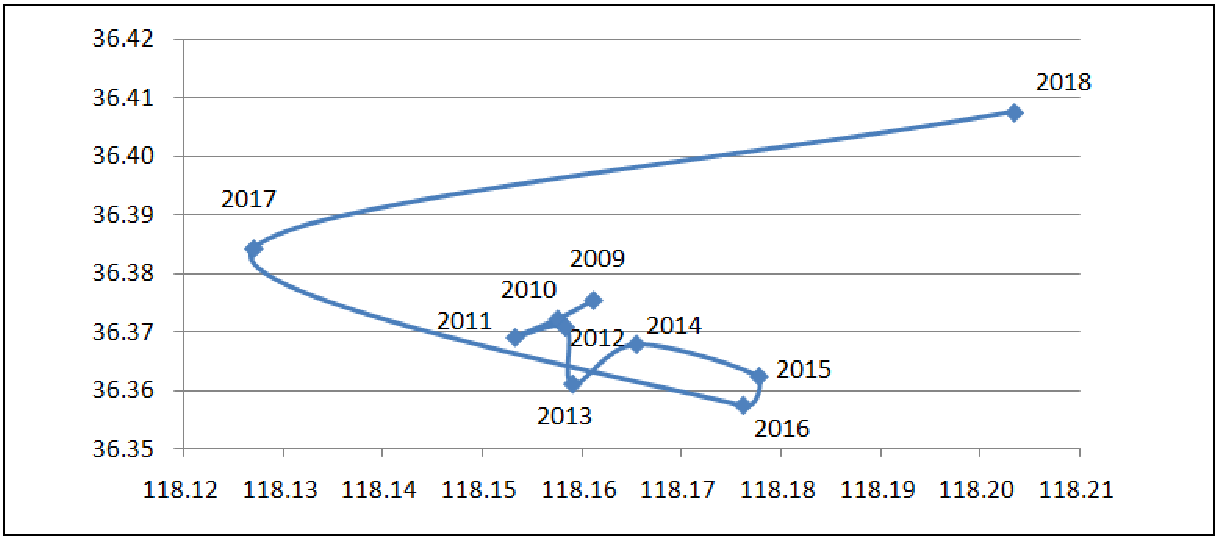

Figure 6. Trajectory of center of gravity for AGTFP in Shandong (horizontal axis represents longitude coordinates and vertical axis represents latitude coordinates)

Source: data derived from calculations by the COG model

5.5 Evolution Characteristics of Regional Difference

As can be seen from Figure 7, the CV of AGTFP in 2009 was 0.017. CV values had increased rapidly after 2014, and reached the maximum in 2016, with a value of 0.122. In 2017 and 2018, the CV values of AGTFP were reduced to 0.059 and 0.060. It can be seen from the figure that although Shandong's AGTFP fluctuated, the overall trend was gradually increasing. This corresponded with the trajectory of Shandong AGTFP, indicating that the AGTFP growth rate difference in Shandong was increasing, and the increase of AGTFP in the eastern and northern regions was relatively large.

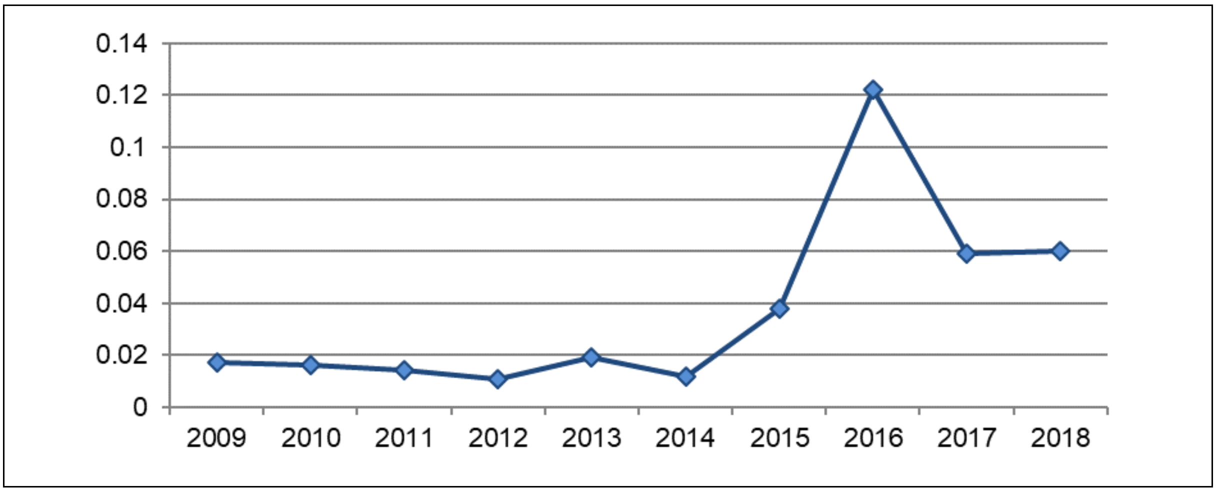

Figure 7. Coefficient of Variation of AGTFP in Shandong province

Source: data derived from calculations by the CV model

5.6 Analysis of the Factors Affecting AGTFP

Besides agricultural technology and agricultural management level, AGTFP was also affected by urbanization level, personal development of farmers, agricultural structure and other factors. In order to identify the factors affecting Shandong's AGTFP, this paper used panel data with a regression analysis of the factors that may affect AGTFP.

Figure 1, Figure 2 and Figure 3 indicate that AGTFP seemed to have spatial correlation. By employing the global Moran's I and local Moran's I analysis methods (Zhang et al., 2020a; Zhang et al., 2020b), we observed that only in 2018 there was a certain degree of spatial autocorrelation. No significant spatial autocorrelation coefficients in the rest of the years. Therefore, our regression analysis did not consider the spatial characteristics of that spatial distribution.

The meanings of each variable can be found in Table 10. The magnitude of the regression coefficients in Table 11 indicates the extent of the independent variables' impact on the dependent variable and does not imply causality. Correlation analysis and collinearity diagnostics were conducted among the independent variables, and no correlations exceeding 0.5 were identified. Furthermore, there was no evidence of multicollinearity among the independent variables. Hausman tests for both fixed effects and random effects were performed on the data, p=0.0003, the p value was less than 0.5 meaning fixed effects was preferred. It can be seen from Table 11 that the p values of *urban*, *agstr*, *PGDP* and *fina* were all greater than 0.1 which failed the significance test, indicating that these factors had no significant impact on AGTFP. *dist* was ignored directly and did not participate in calculation, indicating that distance to the port had no influence on Shandong AGTFP. The p value of *ind* was 0.000, indicating that the industrialization had a significant negative effect on AGTFP. This suggests a strong correlation between the two variables. The p value of *pd* was 0.078, indicating that personal development of farmers had a certain positive effect on AGTFP, indicating there is a certain level of correlation between the two variables. This is consistent with the conclusion in Zuo (2019) that "agricultural human capital and agricultural total factor productivity are significantly positively correlated".

Table 10. Description of the variables in regression analysis

Variable	Variable Description
agtfp	Agricultural Green Total Factor Productivity
urban	Urbanization level
ind	Industrialization
agstr	Agricultural operation structure
PGDP	Per capita GDP
fina	Proportion of fiscal expenditure on agriculture, forestry and water resources to the fiscal expenditure
pd	The proportion of farmers' expenditure on education, culture and entertainment in their annual consumption expenditure
dist	The distance from Qingdao
cons	Constant term of the regression equation

Source: this table was compiled based on the variables used in the regression analysis of the study.

Table 11. Regression results of the factors affecting AGTFP

agtfp	Coef.	Std.Err.	t	P >t	[95% conf.	Interval]
urban	-0.086	0.090	0.950	0.341	-0.235	0.063
ind	-1.170	0.246	4.760	0.000	-1.578	-0.763
agstr	0.048	0.114	0.420	0.674	-0.140	0.236
PGDP	0.092	0.224	0.410	0.681	-0.279	0.463
fina	-0.022	0.338	0.060	0.949	-0.582	0.539
pd	0.571	0.322	1.770	0.078	0.038	1.105
dist	0. 000	(omitted)				
cons	1.590	0.220	7.220	0.000	1.225	1.954

F = 2.18 prob > F = 0.0079

Source: data obtained from the calculations using apanel regression model

6 Discussion

This paper presents an analysis of AGTFP in Shandong Province, quantifying pollutants from fertilizers, livestock, and crop waste in agricultural non-point source pollution. Important factors were also determined by regression analyses. Our results indicate:

(1) Based on the AGTFP data, approximately half of the cities had an AGTFP value equal to 1 each year, indicating high efficiency. The remaining cities were mostly in a state of moderate efficiency or inefficiency. Therefore, there was still significant room for improvement in AGTFP in some areas of Shandong province every year. In terms of regional distribution, the more efficient cities are mostly located in coastal areas and the central region.

(2) From the perspective of dynamic analysis, Shandong province's AGTFP has been constantly improving. The cities with rapid growth include Binzhou, Zibo, Jinan, and Weihai, while the cities with slower growth include Zaozhuang, Laiwu, and Taian. There were significant regional differences in AGTFP growth. From the data in Table 8 it can be observed that the value of *techch* is generally greater than 1, while *effch* varies, with some values greater than 1 and some values less than 1. This indicates that the progress of agricultural technology level is the main driver of AGTFP improvement, a conclusion consistent with previous research by Kumar et al., 2008； and Sheng et al., 2020. On the other hand, the agricultural management level still needs to be enhanced. This result reminds us to pay attention to agricultural management by adopting advanced information technology, accelerating land transfer, and implementing other measures to further enhance AGTFP.

(3) In terms of spatial disparity, the difference in AGTFP growth rates among cities had been increasing year by year. Based on the annual Malmquist index values, the 17 cities in Shandong province can be classified into three types: (1) Continuous growth, with an index greater than 1 every year, consisting of 8 cities; (2) Gradual growth, with an index transitioning from less than 1 to greater than 1, consisting of 3 cities; (3) Fluctuating growth, with an index mostly greater than 1 but occasionally less than 1, consisting of 6 cities. The results of the CoG model indicate that faster growth mainly occurred in the eastern and northern regions. This phenomenon leads us to pay attention to the development speed of AGTFP in the western and southern regions in order to achieve a more balanced AGTFP distribution.

(4) Our research results indicate that the level of urbanization has no significant impact on AGTFP in Shandong province. This finding differs from the conclusion drawn by Li et al. (2021), who suggested a U-shaped relationship between urbanization and agricultural TFP in China. The discrepancy in research findings may be attributed to variations in the geographical scope of the studies. China encompasses over 30 provincial-level administrative regions with varying levels of development, which can lead to divergent conclusions due to differences in statistical data. In the case of Shandong province, the agricultural industrial structure was found to have an insignificant effect on AGTFP. This finding contrasts with previous research by Han et al. (2018) and Yang et al. (2019), who suggested that adjustments in agricultural industry structure have a negative impact on agricultural TFP. The reason for this difference is that the statistical data for Shandong province showed that the variation in grain crop sowing area was not significant during the study period, leading to the conclusion that the agricultural industry structure index had an insignificant impact on AGTFP. Similarly, financial support for agriculture in Shandong province was found to have an insignificant effect on AGTFP, which aligns with the conclusions of Liang and Xi (2022) and Liang and Long (2015) regarding the relationship between financial support for agriculture and agricultural TFP. This suggests that increasing financial support for agriculture may not be conducive to improving AGTFP (Wang et al., 2022).

However, the industrialization of cities and the personal development of farmers were found to have a significant impact on AGTFP. The industrialization of cities was observed to have a negative effect on AGTFP. This is attributed to the migration of a substantial number of young and middle-aged rural laborers from agriculture to the secondary and tertiary sectors as industrialization progresses, resulting in a shortage of labor in rural areas (Xu et al., 2022). Hence, this exodus of rural labor negatively impacts rural TFP. This conclusion aligns with the findings of Liang and Xi (2022) on AGTFP in Shandong Province, where they suggested that industrial development can create a certain siphoning effect on agricultural production factors, which is detrimental to the improvement of AGTFP. The conclusion that the personal development of farmers has a significant impact on AGTFP aligns with the findings of Paudel et al. (2004), who demonstrated a significant relationship between agricultural productivity and the quality of human capital across different states in the United States. Additionally, it corresponds to the results of Yang et al. (2022) in their study on the relationship between agricultural productivity and rural human capital in China. This suggests that improving the education level of farmers can contribute to the enhancement of AGTFP (Reimers and Klasen, 2013).

The aforementioned research results underscore the regional variation in the factors influencing AGTFP. This aligns with the findings of Zhao et al. (2022) and Yang et al. (2019). To improve AGTFP in a specific region, it is imperative to conduct a thorough analysis of the local context and avoid adopting practices from other regions indiscriminately. The panel data regression results highlight the significance of mitigating the negative impact of industrialization and enhancing the quality of the labor force as crucial factors influencing AGTFP.

7 Conclusion and Suggestions

7.1 Conclusion

In order to promote the sustainable development of agriculture, this paper studied the AGTFP of Shandong province. Through this study, we have discovered that the calculation of AGTFP with the inclusion of undesirable outputs yields lower results compared to calculations without considering undesirable outputs. We have found regional disparities in AGTFP within Shandong province, with approximately half of the regions consistently operating at medium to low efficiency levels each year. Over the study period, Shandong's AGTFP displayed an uninterrupted upward trajectory.

The decomposition results of the Malmquist index indicate that the regional disparities in AGTFP within Shandong province were primarily influenced by the efficiency change component (*effch*), highlighting the need to improve management practices in the agricultural development process. By utilizing AGTFP gravity calculations, we observed spatial variations in AGTFP efficiency, with the AGTFP gravity center shifting towards the east and north.

In our panel regression analysis, we found that industrialization and the personal development of farmers have a significant impact on AGTFP. Therefore, there are opportunities to mitigate rural labor outmigration by enhancing rural public services, thereby improving the living conditions of farmers through better healthcare, education, transportation, and other essential amenities. Additionally, the development of the agro-processing industry and the implementation of rural tourism initiatives can help in this regard. Enhancing the personal development of farmers through technical training and educational programs can also contribute to improving AGTFP.

The findings of this research can provide valuable insights for the agricultural green development in Shandong and China as a whole.

Due to limitations in data availability, our analysis of factors influencing AGTFP may not be exhaustive. In the future, we will continue to collect data and delve deeper into the exploration of factors affecting AGTFP, providing more informed recommendations for its improvement.

7.2 Suggestions

In order to improve Shandong AGTFP and promote regional sustainable development and to balance the province-wide development, this paper proposes:

(1) Improve agricultural management and efficiency and reduce extensive management. Reducing factor inputs, especially fertilizers and pesticides, can not only improve efficiency, but also reduce pollution. Advanced technology should be adopted for farmland irrigation to reduce waste.
(2) Focus on industrial structure transformation, improve the efficiency of the primary industry and reduce pollution, and emphasize on developing projects with low pollution emissions and high efficiency, such as agricultural sightseeing tourism and ecological agriculture.
(3) Improve the personal development of farmers. By improving the level of agricultural technology and management through the enhancement of farmers' personal development, the overall efficiency and productivity of agricultural operations can be significantly enhanced, ultimately leading to improved AGTFP.

Acknowledgements

Thanks to the peer reviewers and journal staff for their valuable suggestions and diligence work in improving the paper for publication.

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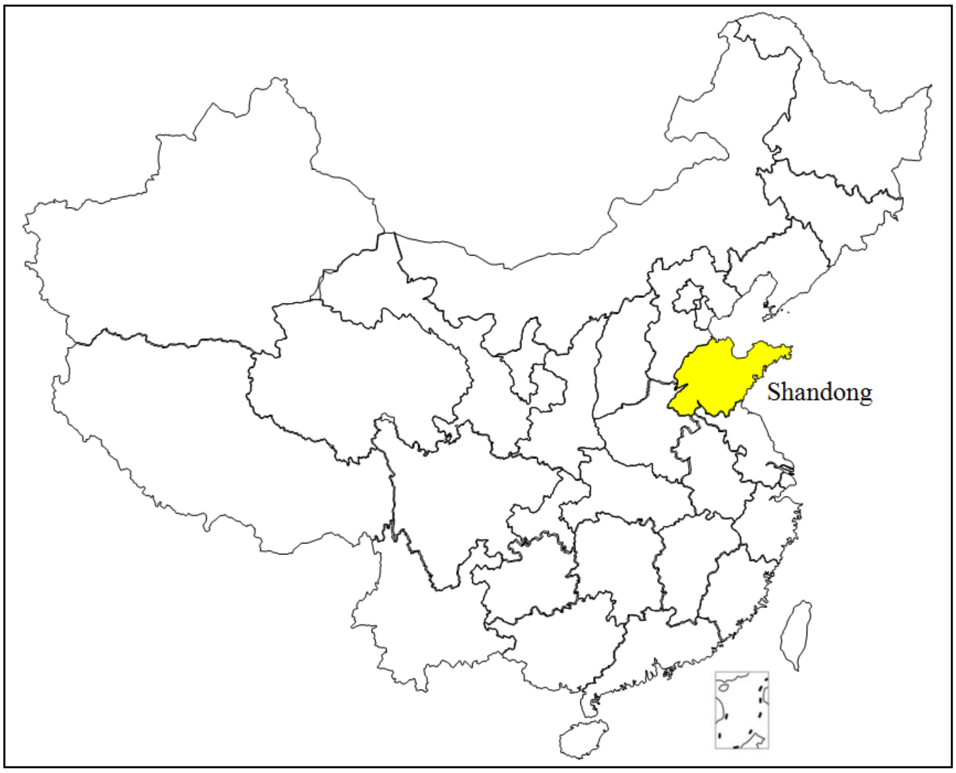
APPENDIX A. Location of Shandong Province, China



Source: drawn according to the map of China

APPENDIX B. Descriptive Statistics of the Variables in the Study

Variable category	Variable	Minimum	Maximum	Average	Standard deviation
Output variable	Agricultural GDP (10,000 Yuan)	279800.000	4121739.641	1987130.638	938386.651
	Pollution (ton)	120436.448	5044.401	41821.734	25365.342
Input variable	Agricultural labor population (ten thousand)	34.908	575.500	236.790	127.279
	Total power of agricultural machinery (kilowatt)	847346.000	15228871.000	6808391.740	3856770.653
	Cultivated land area (hectare)	145590.000	8145541.000	718326.653	627208.540
	Fertilizer (ton)	35162.872	582661.000	271433.521	148665.795
	Irrigated land area (1000 hectare)	33.410	611.890	264.158	151.874
Regression variable	Urbanization ratio (%)	19.592	73.674	51.443	13.126
	Industrialization (%)	35.900	73.900	51.802	6.787
	Agricultural production structure (%)	40.676	89.995	69.569	9.095
	Economic development level (10,000 Yuan)	1.019	19.117	6.411	3.459
	The influence of govern-ment on agriculture (%)	1.273	17.242	11.166	2.753
	Personal development of farmers (%)	4.801	13.327	9.175	2.168
	Distance from port (km)	59.94	456.70	254.259	105.031

Source: the results obtained from the analysis of statistical data.