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Evaluation and Influencing Factors of China's Agricultural Productivity from the Perspective of Environmental Constraints

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Abstract: Based on provincial panel data for the past 15 years in China, the SBM-ML index method was used to measure agricultural productivity under the environmental-constraint perspective with agricultural surface source pollution as the non-desired output. A dynamic panel regression model was used to empirically analyze the factors influencing agricultural productivity to provide a reference for formulating policies to alleviate the conflict between economic development and environmental pollution. The results show that the green total factor productivity of Chinese agriculture exhibits a slow, incremental trend year by year. The growth of green total factor productivity in agriculture mainly comes from the increase in the rate of green technological progress. In terms of geographical disparity, the eastern, central, and western regions show a high-to-low gradient of agricultural green total factor productivity. Agricultural green total factor productivity showed a significant positive spatial correlation in some years. As for the influencing factors, foreign trade in agricultural products is conducive to enhancing green total factor productivity in agriculture, whereas foreign direct investment in agriculture and agricultural technology input inhibit the growth of green total factor productivity in agriculture. This research also found a significant U-shaped relationship between environmental management inputs and green total factor productivity in agriculture. Accordingly, suggestions are provided to optimize the international trade structure of agricultural products, selectively introduce high-quality green foreign investment projects, drive the efficiency of R&D investment through digital technology, and increase investment in special funds for agricultural pollution control.

Keywords: environmental constraints; agriculture; total factor productivity; agricultural surface source pollution; green production

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1. Introduction

The ravages of the novel coronavirus pandemic pose a new challenge to vulnerable agriculture. A 2021 report by the Food and Agriculture Organization of the United Nations (FAO) states that 720–811 million people worldwide faced hunger in 2020, which represents an increase of 161 million compared to 2019 [1]. The COVID-19 pandemic is just the tip of the iceberg; more alarmingly, the pandemic has exposed vulnerabilities forming in agricultural systems in recent years as a result of major drivers, such as conflict, climate variability, and economic slowdowns and downturns. In the current situation, with many changes are emerging in global development, it is imperative to enhance agricultural resilience, promote green production, and explore the major drivers affecting agricultural productivity.

Since reform and opening up, Chinese agriculture has managed to feed more than 20% of the world's population with less than 10% of the world's arable land [2]. The "green revolution" in agriculture centered on high-yielding seeds and the improvement of irrigation and fertilization technology. However, this success has meant that agricultural development may have come at an environmental cost. Economic growth has been accompanied by excessive use of pesticides, fertilizers, agricultural films, and other chemicals, leading to severe soil contamination, declining land strength, and water pollution. According to the data of the National Bureau of Statistics, in 2019, fertilizer, agricultural film, and pesticide inputs reached 54.036 million tons, 2.408 million tons, and 1.391 million tons, respectively, with an increase of 24.5%, 57.3%, and 6.1%, compared with 2002 [3]. Agriculture has become a major source of chemical oxygen demand (COD), as well as total nitrogen (TN) and total phosphorous (TP) emissions, which indicates that agricultural development should fully consider its resource carrying capacity and the environmental disasters that may result.

In order to realize the transformation from traditional agriculture to modern agriculture, China must rely on the improvement of factor input efficiency, optimization of production factor combination methods, technological progress, organizational and institutional innovation, etc., which means that the growth of agriculture depends on the total factor productivity (TFP). TFP, which can measure economic performance that accounts for the influences of technical progress and efficiency, was proposed by Solow (1957) [4]. This source of labor productivity increase can offset the adverse effects of diminishing returns to capital and is an enduring engine of economic growth. In opposition to traditional total factor productivity analysis, this paper adopts a non-radial, non-perspective slack-based model (SBM) and a Malmquist (ML) index that considers non-consensual output and incorporates resources, environment, and development into a unified analytical framework to evaluate China's agricultural productivity from the perspective of environmental constraints, which is not only important for establishing a mechanism to objectively exam the agricultural growth model ,but also provides the government with an opportunity to practice the "resource-saving and environment-friendly society" concept.

2. Literature Review

From a methodological point of view, previous studies of agricultural TFP mostly adopted parametric and non-parametric analysis [5–8]. Grilliches (1957) [9], Alston et al. (1998) [10], McCunn and Huffman (1998) [11] (for US agriculture), Hayami and Rutta (1970) [12] (for Japanese agriculture), Rosegrant and Evenson (1992) [13] (for Indian agriculture), and Coelli and Rao (2005) [14] conducted cross-country comparisons of agricultural TFP. Lin (1992) [15] used the traditional growth accounting method to analyze the growth of agricultural TFP and found that Chinese agricultural TFP increased dramaticallyfrom 1978 to 1984 and contributed 48.64% to total agricultural output. Agricultural outputs and inputs then fell sharply between 1984 and 1987, with TFP increasing by only 2.05% during this period. Fan and Pardey (1997) [16] also used the growth accounting approach to analyze the sources of growth in total agricultural output between 1965 and 1989 and found that technological and efficiency improvements resulting from a series of institutional reforms introduced in the late 1970s contributed only 14% to the growth of total agricultural output in China. Gong (2018) [8] states that there are significant cyclical fluctuations in agricultural TFP growth in China, with six periods. The third and fifth reform periods (1990–1993 and 1998–2003) achieved higher productivity growth than the first reform period (1978–1984), whereas the second and sixth reform periods (1985–1989 and 2004–present) experienced low growth. Regarding the influencing factors of agricultural TFP, the current literature mostly looks at the motivations such as agricultural financial support [17], the education level of farmers [18], openness to the outside world [6,7], land–resource mismatch [19], etc.

The above-mentioned studies are important for a deeper understanding of the relationship between agricultural development and resource constraints, but few of them address environmental factors. Studies on agricultural development and environmental pollution have been developed along another main line: the environmental Kuznets curves (EKC) hypothesis, which was proposed by Grossman and Krueger (1992) [20].Earlier studies, such as those by Antle and Heidebrink (1995) [21] and Mc Connell (1997) [22], analyzed the relationship between economic growth and agricultural pollution at the theoretical level, suggesting that the relationship between agricultural surface pollution and economic development may also be consistent with the EKC. However, the EKC test has the following problems: on the one hand, it is difficult to incorporate resource constraints into the analysis framework, and on the other hand, pesticides, fertilizers, and agricultural films are not only pollutants but also agricultural inputs. Therefore, this relationship leads to endogenous problems with the EKC test.

Agricultural production yields economic outputs with environmental pollution, such as fertilizer and pesticide runoff, whereas a traditional TFP analysis that does not include environmental pollution would make the assessment results-biased. Based on studies related to agricultural TFP and EKC, scholars have gradually shifted their research focus from agricultural TFP to agricultural green TFP. Agricultural green TFP is agricultural TFP regarding resource and environmental constraints. Ball et al. (2001) [23] and Rezek and Perrin (2004) [24] measured TFP in US agriculture from the perspective of environmental constraints and found that the TFP index accounting for environmental pollution was lower than the TFP index without accounting for environmental pollution. Wang Qi et al. (2012) [25] measured the green TFP change index of Chinese agriculture from 1992 to 2010 based on the stochastic frontier production function analysis using nitrogen and phosphorus loss in agricultural production as factor inputs and found that the average annual growth rate of green TFP and TFP during the study period were basically the same. Li Gucheng (2014) [26] analyzed the growth of agricultural green TFP in China by combining the directional distance function (DDF) model and the Malmquist index, and the results were consistent, both models concluding that agricultural green TFP was generally lower than agricultural TFP and that green TFP was higher in the eastern region than in the central and western regions. With regard to the factors influencing green TFP in agriculture, literature has been developed from the perspectives of human capital [27,28], fiscal expenditure [29], agricultural technology inputs [30], agricultural industry structure [31] etc.

In summary, existing studies on the relationship between economic development and environmental pollution have difficulty incorporating resource constraints into the analytical framework. Hence, research on agricultural TFP may overestimate agricultural productivity by ignoring the effects of agricultural pollution. Most of the few studies on green TFP in agriculture have focused on the plantation, vegetable, or food industry, and there are fewer comprehensive evaluations of green TFP in agriculture. To measure the non-desired output of agriculture, some scholars have used indicators such as carbon emissions from agricultural production [32,33], ignoring the impact of surface source pollution in agricultural production. Therefore, this research attempts to make the following extensions and contributions: measurement of agricultural surface source pollution output by the unit-survey assessment method to compensate for the lack of estimation of agricultural pollution emissions; measurement of agricultural productivity from the perspective of environmental constraints to obtain more accurate productivity measurement results; analysis of the driving factors affecting agricultural productivity to provide a theoretical basis for the government to implement targeted policies.

3. Evaluation of China's Agricultural Productivity from the Perspective of Environmental Constraints

In this paper, we used the unit-survey assessment method to account for agricultural surface source pollution and used the accounting results as non-desired outputs into the ML index based on the SBM directional distance function to measure agricultural productivity from the perspective of environmental constraints, i.e., green TFP. This section introduces the unit-survey evaluation method, the ML index based on the SBM directional distance function, and an exploratory spatial data analysis method.

3.1. Unit-Survey Evaluation Method

There are three main methods accounting for agricultural surface source pollution. First, fertilizer, pesticide, and agricultural film applications are used as agricultural environmental pollution variables, which cannot objectively reflect the degree of pollution due to varying sewage effects of the above agricultural inputs in different production modes. Second, the theory of nutrient balance is applied to measure the total amount of excess nitrogen; however, this method ignores the agricultural surface source pollution of other pollution elements. Third, the unit-survey and assessment method of the Department of Environmental Science and Engineering of Tsinghua University is used to measure the amount of discharge. This method accounts for total pollution production by investigating the amount of discharge from different agricultural pollution units and the coefficients affecting agricultural surface pollution. The accuracy of the final pollution accounting may be affected by the collection of emission factors from different sources and continuous changes, but in general, this is a more advanced method of accounting for agricultural surface pollution. This paper draws on this methodology to conduct a literature survey to establish the correspondence between agricultural activities and emissions.

A process of accounting for agricultural surface source pollution is proposed as follows. First, identification of surface source types and pollution production analysis are established. Identifying the main types of surface source pollution and determining the scope of investigation of pollution-producing units is the basis for subsequent assessment. The traditional cycle of material and capacity between planting and farming is broken by the specialization and regionalization of modern agriculture. Under the production mode of "high input, high output and high emission", a large amount of waste cannot be effectively used and pollutes the groundwater. In addition, waste pollution and sewage pollution in rural life also put pressure on the ecological environment. Therefore, this paper focuses on four pollution sources: farm fertilizer, livestock farming, farm solid waste, and rural living. The main pollutants accounted for are TN, TP, and COD. Second, unit determination and statistical survey on the basis of the analysis and decomposition of agricultural surface pollution sources are conducted to establish the basic units of the survey. Survey unit refers to an independent unit that produces pollutants and has a certain contribution rate to surface pollution. Third, in the process of investigating and analyzing the pollution generation process, quantitative analysis of the main sources of pollutant loss is the basis for determining the emission factor values of each unit, which are obtained mainly through the method of literature research. Finally, emissions and emission intensity of various surface source pollutants are estimated.

After obtaining the statistical indicators of each pollution producing unit and the production and discharge coefficients, we drew on the idea of Chen et al. (2006) [34] to account for agricultural surface source pollution emissions. The accounting formula is shown in Equation (1).

$$Ej = \sum EUi\rho ij(1-\eta i)Cij(EUij,S) \ = \sum PEij\rho ij \ \ (1-\eta i) \ \ Cij(EUij,S) \qquad (1)$$

In Equation (1), E_j is the emissions of agricultural pollutants TN, TP, and COD in each province; EU is the index statistics of each source of pollution; ρ_{ij} is the pollution production intensity factor of pollutant j of unit I; ηi is a coefficient characterizing the efficiency of the relevant resource use; $PEij$ is the amount of pollutant j generated, Cij is the emission factor for pollutant j of cell i and is determined by the cell and spatial feature.

3.2. SBM Directional Distance Function and ML Index

In order to overcome the biased results caused by ignoring slack variables and focusing on only one aspect of inputs or outputs when evaluating productivity, Tone (2001) [35] proposed the SBM model. The proposed model incorporates slack variables into the objective function to address both the inefficiency factor caused by slack and the inclusion of non-desired output in the productivity evaluation system. The SBM model is dimensionless and angle-free, avoiding the bias caused by different dimensions and angle differences, and its measurement results are more accurate. The basic form of the SBM model is shown in Equation (2).

$$\begin{gathered}\vec{D}_0^{t}(x^{t,k\prime},y^{t,k\prime},u^{t,k\prime};g)=Min\rho=\frac{1-\frac{1}{N}\sum\limits_{n=1}^{N}S_n^x/x_{n0}}{1+\frac{1}{M+I}(\sum\limits_{m=1}^{M}S_m^y/y_{m0}+\sum\limits_{i=1}^{I}S_i^u/u_{i0})}\\ s.t.\sum_{k=1}^{K}z_kx_{nk}+S_n^x=x_{n0},n=1,2,\ldots,N;\sum_{k=1}^{K}z_ky_{mk}-S_m^y=y_{m0},m=1,2,\ldots,M;\\ \sum_{k=1}^{K}z_k=I;\sum_{k=1}^{K}z_ku_{mk}+S_i^u=u_{i0,}i=1,2,\ldots,I;z_k\geq 0;S_n^x\geq 0;S_m^y\geq 0;S_i^u\geq 0\end{gathered} \tag{2}$$

In Equation (2), D_0 is the directional distance function; x indicates input; y indicates the desired output; u indicates non-desired outputs; Direction vector g shows that the desired and undesired outputs are increased or decreased in the same proportion for a given input; t indicates period; k indicates the number of decision units; Z indicates the respective weights when constructing environmental technologies; and S_n^x, S_m^y, and S_i^u represent the slack vectors for input redundancy, desired output deficiency, and excessive environmental pollution emissions, respectively. When S_n^x, S_m^y, and S_i^u are all greater than zero, the actual inputs and pollution are greater than the inputs and pollution emissions at the boundary, whereas the actual output is less than the output at the boundary. The model is a directional distance function with variable returns to scale (VRS) or, if the sum of the weight variables, $\sum\limits_{k=1}^{K} z_k = 1$, is removed, the model becomes a directional distance function with constant returns to scale.

The economic meaning of ρ in the SBM directional distance function represents the inefficient ratio of inputs to outputs that strictly decreases with respect to S_n^x, S_m^y, and S_i^u. When ρ = 1, the production unit is fully efficient, and there is no excess of inputs and undesired outputs or deficiency of desired outputs; when ρ < 1, it there is an efficiency loss in the production unit, and the efficiency can be improved by reducing the amount of inputs and undesired outputs in combination. The sources of green technical inefficiencies are usually input redundancy, agricultural output deficiencies, and agricultural surface source pollution redundancy.

The technical efficiency of green agriculture, measured by SBM, is a static analysis that can only reflect the relative relationship between provinces and production boundaries. The ML productivity index, on the other hand, allows for a dynamic analysis of each province's position relative to the production frontier (efficiency change) and movement toward the production frontier (technological progress). According to the method of Chung et al. (1997) [36], the ML index from period t to t + 1 can be expressed in the following form.

$$ML_t^{t+1}=\left[\frac{1+\vec{D}_0^{t}(x^t,y^t,u^t;g)}{1+\vec{D}_0^{t}(x^{t+1},y^{t+1},u^{t+1};g)}\times\frac{1+\vec{D}_0^{t+1}(x^t,y^t,u^t;g)}{1+\vec{D}_0^{t+1}(x^{t+1},y^{t+1},u^{t+1};g)}\right]^{\frac{1}{2}} \tag{3}$$

$$MLTECH_t^{t+1}=\left[\frac{1+\vec{D}_0^{t+1}(x^t,y^t,u^t;g)}{1+\vec{D}_0^{t}(x^t,y^t,u^t;g)}\times\frac{1+\vec{D}_0^{t+1}(x^{t+1},y^{t+1},u^{t+1};g)}{1+\vec{D}_0^{t}(x^{t+1},y^{t+1},u^{t+1};g)}\right]^{\frac{1}{2}} \tag{4}$$

$$ML_t^{t+1}=MLTECH_t^{t+1}\times MLEFFCH_t^{t+1} \tag{5}$$

$$MLEFFCH_t^{t+1}=\frac{1+\vec{D}_0^{t}(x^t,y^t,u^t;g)}{1+\vec{D}_0^{t+1}(x^{t+1},y^{t+1},u^{t+1};g)} \tag{6}$$

In Equations (3)–(6), D_0 indicates the directional distance function; x indicates input; y indicates desired output; u indicates non-desired output; the directional vector, g, indicates that the desired and undesired outputs are increased or decreased in the same proportion for a given input; and t indicates the period. The ML index can be decomposed into technical progress rate (MLTECH) and technical efficiency (MLEFFCH) where the technical progress rate measures the rate of progress of the green technology frontier, i.e., the dynamic change of the outward expansion of the generation possibility frontier; and the technical efficiency reflects the speed of catching up with the production possibility frontier, which can be decomposed into scale efficiency and pure technical efficiency. The ML index is usually used to measure and decompose the green TFP. Indices such as ML, MLTECH, and MLEFFCH greater than 1 reflect the progress of green TFP, green technological progress rate, and green technological efficiency, respectively, whereas values less than 1 reflect their decline.

3.3. Exploratory Spatial Data Analysis Method

Due to the relatively similar social, economic, and ecological attributes, the proximity of geographic units exhibits a certain spatial correlation. In order to further grasp the spatial association and interaction characteristics among spatial units, the global Moran index was used to describe the average level of green TFP association between all spatial units and its significance. The calculation formula is as follows:

$$I = \frac{n\sum\limits_{i=1}^{n}\sum\limits_{j=1}^{n} w_{ij}(x_i - \bar{x})(x_j - \bar{x})}{\sum\limits_{i=1}^{n}\sum\limits_{j=1}^{n} w_{ij}\sum\limits_{i=1}^{n}(x_i - \bar{x})^2} \tag{7}$$

In Equation (7), $\overline{x} = \frac{1}{n}\sum\limits_{i=1}^{n} x_i$, x_i, and x_j indicate the observations in region i; and year j, n is the number of regions. In this paper, the spatial weight matrix, w, was used based on the adjacency matrix, and w_{ij} takes the value of 1 when region i and year j are adjacent—otherwise, it is 0, where Hainan is set as adjacent to Guangdong. The value interval of I is $[-1,1]$. The closer I is to 1, the stronger the spatial positive correlation between regions, indicating higher similarity of spatial distribution of a certain crop yield in neighboring regions; the closer I is to -1, the stronger the spatial negative correlation between regions; if I is close to 0, there is no spatial autocorrelation between regions. The local Moran index measures the degree of spatial difference between each spatial unit and its surrounding spatial units, as well as its significance. The calculation formula is as follows:

$$I_i = \frac{(x_i - x)}{S^2}\sum_{j=1}^{n} w_{ij}(x_j - x),\ i \neq j \tag{8}$$

In Equation (8), $S^2 = \frac{1}{n}\sum\limits_{i=1}^{n}(x_i - \overline{x})^2$. The rest of the symbols have the same meaning as in Equation (7). The Moran scatter plot and LISA agglomeration plot can be used to analyze the degree of continuous production of a certain crop and its distribution area. The contiguous distribution was divided into four main types, namely high–high (HH), low–low (LL), high–low (HL), and low–high (LH) clustering.

3.4. Variables and Data

This paper used the SBM-based directional distance function method to measure green total factor productivity in agriculture and decomposes its structure into four components: green technological progress rate, green technology efficiency, scale efficiency, and pure technical efficiency. In this paper, for the agricultural green TFP measure, data from 30 provinces across China (excluding Hong Kong, Taiwan, Macau, and Tibet, considering data availability and smoothness) from 2002–2016 were selected for the empirical study. The data used for the analysis were obtained from the China Agricultural Statistical Yearbook, provincial statistical yearbooks and the EPS data platform. In this paper, the above 30 provinces were divided into three major regions, namely the eastern, central, and western regions, according to the traditional division method. The current generally accepted division of the eastern and western regions is as follows: the eastern region includes Beijing, Tianjin, Hebei, Liaoning, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong, Guangxi, and Hainan; the central region includes Shanxi, Inner Mongolia, Jilin, Heilongjiang, Anhui, Jiangxi, Henan, Hubei, and Hunan; the western region includes Sichuan, Chongqing, Guizhou, Yunnan, Shaanxi, Gansu, Qinghai, Ningxia, and Xinjiang.

With reference to existing studies, expected output was treated with the gross output value of agriculture, forestry, animal husbandry, and fishery as the output variables, whereas the value-added index of primary industry (2002 = 100) was used to remove the effect of price factors. The non-desired output was measured as the total TN, TP, and COD emitted from agricultural surface source pollution in each province. The selected input variables were total power of agricultural machinery, fertilizer application, crop sowing area, and number of people employed in the primary industry, which are closely related to agricultural production. The value added of primary industry, total agricultural surface pollution discharge, total power of agricultural machinery, agricultural fertilizer, crop sown area, number of farm animals, and number of people employed in primary industry are denoted by GDP, E, Mach, Chem, Land, Cattle, and Labor, respectively. Descriptive statistics for the variables are shown in Table 1.

Table 1. Descriptive statistics of variables.

Variables	Description	Unit	Obs	Mean	Std.Dev	Min	Max
GDP	Value added of primary industry	RMB 100 million million Yuan	450	1471.26	1131.93	65.50	5409.56
E	Agricultural surface pollution discharge	million tons	450	100.71	81.94	7.91	360.79
Mach	Agricultural machinery	million kilowatts	450	2839.71	2735.26	95.30	13,353
hem.	Agricultural fertilizer	million tons	450	177.30	138.85	6.60	716.10
Land	Crop sown area	thousands of hectares	450	5294.39	3551.41	151.40	14,472.30
Cattle	Number of farm animals in primary industry	million heads	450	388.63	316.63	1.23	1512.83
Labor	Number of people employed in primary industry	million people	450	990.03	712.95	36.35	3403.60

3.5. Analysis of China's Agricultural Productivity from the Perspective of Environmental Constraints

In this section, the ML index based on the SBM directional distance function was used to measure and decompose the agricultural green TFP, followed by spatial data analysis to explore its spatial correlation.

3.5.1. Measurement Results of Green TFP in Agriculture

First, we calculated the average value of agricultural green TFP and its decomposition in 30 Chinese provinces from 2002 to 2016 with the SBM-ML index method, and the specific results are shown in Table 2. The overall results show that the average value of the national agricultural green TFP index is greater than 1, with an increasing trend year by year, which indicates that China's agricultural green TFP is growing every year. The national average value of green TFP in agriculture is 1.052, indicating that the average annual growth rate of green TFP in agriculture is 5.22%. The green efficiency of agriculture decreased by 3.97%, and the rate of green technological progress in agriculture increased by 9.52%. The growth of green TFP in agriculture mainly comes from the increase in the level of green technological progress. Pure technical efficiency decreased by 2.01%, and scale efficiency decreased by 2.08%.

Table 2. Average green total factor productivity and decomposition values by province, 2002–2016.

Province	Green Technology Efficiency	Green Technological Progress Rate	Pure Technical Efficiency	Scale Efficiency	Green TFP
Beijing (BJ)	1.000	1.164	1.000	1.000	1.164
Tianjin (TJ)	0.953	1.096	0.932	1.024	1.045
Hebei (HB)	0.963	1.093	0.982	0.979	1.052
Shanxi (SX)	0.977	1.093	1.007	0.968	1.067
Inner Mongolia (NM)	0.926	1.098	0.953	0.969	1.017
Liaoning (LN)	0.951	1.096	0.965	0.984	1.042
Jilin (JL)	0.933	1.091	0.955	0.975	1.018
Heilongjiang (HL)	0.952	1.101	0.981	0.969	1.048
Shanghai (SH)	1.000	1.075	1.000	1.000	1.075
Jiangsu (JS)	0.987	1.095	1.009	0.976	1.080
Zhejiang (ZJ)	0.981	1.110	1.000	0.980	1.089
Anhui (AH)	0.964	1.091	0.987	0.974	1.051
Fujian (FJ)	0.970	1.106	1.000	0.968	1.073
Shandong (SD)	0.968	1.092	1.000	0.966	1.057
Henan (HN)	0.950	1.088	0.950	1.001	1.034
Hubei (HB)	0.968	1.091	1.001	0.965	1.056
Hunan (HN)	0.967	1.090	0.998	0.967	1.054
Guangdong (GD)	0.962	1.093	1.000	0.959	1.051
Jiangxi (JX)	0.952	1.091	0.977	0.972	1.038
Guangxi (GX)	0.966	1.088	0.992	0.972	1.051
Hainan (HI)	0.917	1.103	0.936	0.978	1.011
Chongqing (CQ)	0.961	1.091	0.993	0.965	1.049
Sichuan (SC)	0.964	1.090	0.995	0.967	1.051
Guizhou (GZ)	0.980	1.091	1.022	0.956	1.069
Yunnan (YN)	0.937	1.091	0.963	0.971	1.022
Shaanxi (SN)	0.967	1.088	0.996	0.968	1.052
Gansu (GS)	0.955	1.095	0.986	0.966	1.046
Qinghai (QH)	0.976	1.087	1.000	0.974	1.058
Ningxia (NX)	0.957	1.090	0.875	1.102	1.043
Xinjiang (XJ)	0.928	1.094	0.956	0.968	1.015
National	0.961	1.095	0.980	0.979	1.052

Second, in terms of time-varying dynamics, green TFP, green technical progress rate, green technical efficiency, pure technical efficiency, and scale efficiency all show up- and down trends. In Figure 1, GTFP is green TFP, GTE is green technical efficiency, GTC is green technical progress rate, PE is pure technical efficiency, and SE is scale efficiency. As shown in Figure 1, the ML index is greater than 1, except for 2009, indicating a steady growth trend of agricultural green TFP in general. The rate of technological progress fluctuates considerably, reaching a peak in 2004 and then falling back. Technical efficiency is relatively low—than 1, except for 2011 and 2012.

Third, in terms of regional differences, green TFP in the eastern, central, and western regions shows an upward trend. The average green TFP indices of the eastern, central and western provinces were 1.055, 1.053, and 1.045, respectively, for 2002–2016. Agricultural green TFP showed an upward trend in all regions, with an average increase of 5.54% in the eastern region, 5.30% in the central region, and 4.48% in the western region. The eastern, central, and western regions show a high-to-low gradient of agricultural green total factor productivity. In addition, the increase in green TFP in the eastern, central, and western regions is driven by growth of the green technology advancement rate. The increase in the rate of green technological progress means that the production frontier is pushing outward, driving productivity and compensating for the loss of green technological efficiency. Green TFP and decomposition values for the eastern, central, and western provinces are shown in the Appendix A.

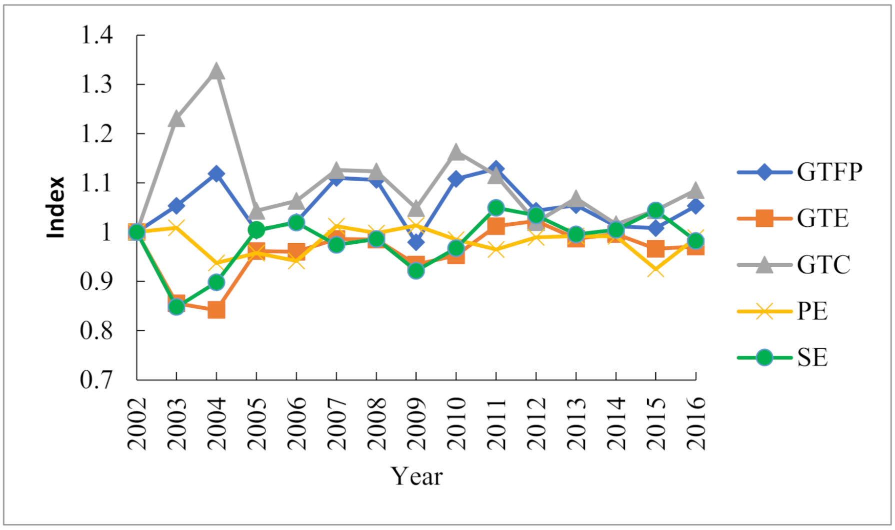

Figure 1. Agricultural green TFP and decomposition values, 2002–2016.

As the estimation results show, the average growth rate of green TFP in the eastern provinces is 5.54%, including a 3.96% decline in technical efficiency and a 9.72% increase in the rate of technological progress. Pure technical efficiency decreased by 6.44%, and scale efficiency decreased by 2.19%. The eastern provinces with the highest green TFP growth rates are Beijing, Zhejiang, Jiangsu, and Shanghai. Tianjin, Liaoning, and Hainan have the lowest green TFP growth rates among eastern provinces.

The average growth rate of green TFP in the central provinces is 5.30%, including a 3.73% decline in technical efficiency and a 9.37% increase in the rate of technological progress. Pure technical efficiency and scale efficiency decreased by 1.46% and 2.46%, respectively. The central provinces with the highest green TFP growth rates are Shanxi, Hubei, and Hunan. The central provinces with the lowest growth rates are Jiangxi, Henan, Jilin, and Inner Mongolia.

The average green TFP growth rate in the western provinces is 4.48%, with a 4.19% decline in technical efficiency and a 9.05% increase in the rate of technological progress. Pure technical efficiency and scale efficiency decreased by 2.46% and 1.89%, respectively. The western provinces with the highest green TFP growth rates are Guizhou, Shaanxi, and Qinghai, and the provinces with the lowest green TFP growth rates are Chongqing, Ningxia, and Yunnan. Similarly to the eastern and central provinces, the western provinces are all driven by technological progress.

3.5.2. Spatial Correlation Analysis of Green TFP in Agriculture

Table 3 shows the spatial correlation of green TFP in agriculture. The global Moran index of agricultural green TFP in 2004, 2006, 2010, 2015, and 2016 passed the significance test, indicating that the above years of agricultural green TFP have significant positive spatial correlation and show a more obvious spatial clustering characteristic.

To further investigate the spatial agglomeration at the local scale, LISA agglomeration analysis was used to study the spatial agglomeration types of each province. As shown in Figure 2, the number of provinces with significant spatial correlation during the study period was low and unstable.

The above results suggest that agricultural green TFP has a spillover effect in some years and that the improvement of green productivity level in a given province may drive a similar improvement in neighboring provinces. However, no obvious agglomeration center was formed, and the spillover effect is not regular.

Table 3. Green TFP Moran global autocorrelation index and test values for Chinese agriculture.

Year	Global Moran Index
2004	0.3148 ***
2006	0.2337 **
2010	0.1674 **
2015	0.1711 **
2016	0.2424 **

Note: ***, ** are significant at the 1%, and 5% levels, respectively; values in parentheses indicate standard errors.

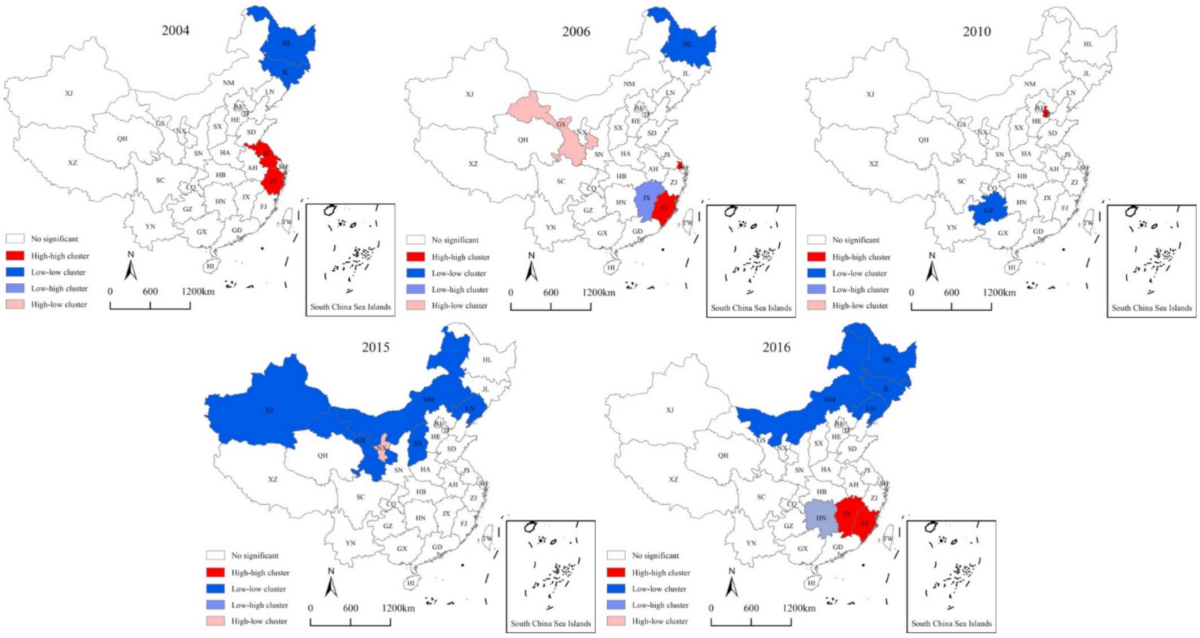

Figure 2. LISA cluster types of green TFP in Chinese agriculture (2002–2016).

4. Empirical Analysis of the Influencing Factors of Agricultural Productivity from the Perspective of Environmental Constraints

4.1. Econometric Models and Research Methods

Coe and Helpman (1995) [37] proposed that the change in a country's TFP in an open economy is influenced by the stock of domestic R&D intellectual capital on the one hand and related to the stock of international R&D intellectual capital on the other; they accordingly proposed a model as follows:

$$\ln Fi = ai^0 + ai^d \ln Si^d + ai^f \ln Si^f \tag{9}$$

In Equation (9), F_i represents TFP, S_i^d represents domestic R&D intellectual capital, and S_i^f represents international R&D intellectual capital spillover. The above international R&D knowledge-spillover model has become a standard paradigm for academics to explore technology spillover effects. This paper extends the model by introducing international trade in agricultural products, foreign direct investment in agriculture, agricultural technology input, agricultural human capital, rural affluence, environmental regulation, and agricultural industry structure to examine the factors influencing green TFP in agriculture.

International Trade in Agricultural Products. The impact of international trade in agricultural products on agricultural green TFP is a combination of the TFP effect and an environmental effect. Agricultural trade may affect agricultural TFP through technology spillovers and may affect the environment through structural, technological, and scale effects. The above effects play a dominant role in determining the direction of the impact of agricultural trade on agricultural green TFP. Thus, the direction of the agricultural trade on green agricultural TFP needs to be further verified.

Foreign direct investment in agriculture. On the one hand, agricultural FDI hinders agricultural TFP due to its competitive effect. On the other hand, regarding the analysis of the environmental effects of foreign direct investment in agriculture, according to the pollution paradise hypothesis, the stringent environmental regulations in developed countries may also force some heavily polluting enterprises and industries to shift their production abroad, putting pressure on the local environment. Therefore, this paper assumes a negative effect of agricultural FDI on agricultural green TFP.

Agricultural technology inputs. According to endogenous growth theory, R&D innovation drives productivity. Green technologies can boost productivity and reduce pollution. Thus, this paper expects a positive effect of agricultural technology inputs on agricultural green TFP.

Agricultural human capital. The increase in the level of human capital significantly raises the level of agricultural TFP. An increase in education is conducive to raising environmental awareness and enforcing appropriate environmental regulations. Therefore, this paper assumes that higher levels of human capital have a positive effect on green TFP in agriculture.

Rural affluence. The level of rural affluence is closely related to the choice of agricultural production methods, the promotion and application of agricultural technologies, and the improvement of agricultural production efficiency. As the per capita income level of farmers increases, people's awareness of environmental protection and environmental regulations increases, accompanied by a reduction in agricultural surface source pollution emissions. Based on the above analysis, this paper expects a positive effect of rural affluence on agricultural green TFP.

Environmental Regulation. The traditional neoclassical economic view argues that in the short run, the implementation of environmental regulations increases the cost of pollution control and has a "crowding-out effect" on other profitable investments, i.e., the "compliance-cost" effect of environmental regulations, thus negatively affecting green total factor productivity. [38]. The modified view represented by Porter et al. (1995) [39] takes a dynamic perspective, arguing that appropriate environmental regulations can encourage producers to adopt cleaner production technologies in the long run, optimize factor allocation efficiency, partially or even fully offset their "compliance costs", and achieve the dual goals of economic growth and environmental protection. This is the "innovation-compensation" effect of environmental regulation. From a dynamic point of view, after a certain period of development, the "innovation-compensation" effect of environmental regulations on green TFP in agriculture will gradually offset the negative impact of the "compliance-cost" effect. In terms of the "innovation-compensation" effect, an increase in the intensity of environmental regulations encourages agricultural producers to apply green production technologies and improve green total factor productivity in agriculture by increasing the value added of agricultural products and reducing agricultural pollution emissions. In this paper, we expect that the effect of environmental regulations on green TFP in agriculture may show a nonlinear effect.

Agricultural industry structure. Industries have differ in resource consumption and pollutant emission intensity. When the proportion of resource-consuming and pollution-intensive industries in the agricultural industry increases or the development rate accelerates, pollution emissions intensify; conversely, when the proportion of such industries in the agricultural industry decreases or the development rate slows, pollution is reduced. Therefore, this paper expects that the rising share of livestock farming in the agricultural industry structure has a hindering effect on the growth of green TFP in agriculture.

Changes in economic factors are often influenced by past behavior patterns. The efficiency of green TFP in agriculture in the one period will have a persistent effect on the next period. Therefore, we constructed a dynamic panel model, which introduces a lagged variable of green TFP to obtain more effective estimation results. This paper draws on previous research to form a model based on the above analysis.

$$\ln GTFP_{it} = a_0 + a_1 \ln GTFP_{it} - 1 + a_2 \ln Trade_{it} + a3 \ln FDI_{it} + a_4 \ln T_{it} + a5 \ln HC_{it} + a6 \ln Inc_{it} + a7 \ln Er_{it} + a8(\ln Er_{it})^2 + a9 \ln Str_{it} + \varepsilon_{it} \quad (10)$$

In Equation (10), $GTFP_{it}$ represents the agricultural green TFP for each province by year, $Trade_{it}$ represents the scale of international trade in agricultural products, FDI_{it} represents the amount of foreign direct investment in agriculture, T_{it} represents the level of agricultural technology inputs, HC_{it} represents the level of human capital, Inc_{it} represents the level of rural affluence, Er_{it} represents environmental regulation, and Str_{it} represents the structure of the agricultural industry.

4.2. Variable and Data

4.2.1. Variable

The agricultural green TFP resulted from the SBM-ML model was a chain change index of 1 in the previous year, which was transformed into a year-on-year cumulative growth index of 1 in 2002 as the dependable variable in the empirical model in this section. The variables are shown in Table 4.

Table 4. Definition of variables and measurement methods.

	Variable Name	Abbreviations	Variable Measurement Method
Dependable variables	Agriculture Green TFP	GTFP	SBM-ML model measurement results
Independent variables	Scale of foreign trade	Trade	Total import and export of agricultural products
	Foreign direct investment	FDI	Amount of agricultural foreign direct investment
	Technology inputs	T	Number of agricultural technicians in public sector enterprises and institutions
	Human capital	HC	Average years of schooling of agricultural labor force by region
	Rural income	Inc	Per capita income of farmers
	Environmental regulation	Er	Total investment in environmental pollution control
	Industry structure	Str	Proportion of the output value of animal husbandry in the total output value of agriculture, forestry, animal husbandry, and fishery

4.2.2. Data Description

Considering the availability and smoothness of data, we selected data from 30 Chinese provinces (excluding Hong Kong, Taiwan, Macau, and Tibet) for the empirical study. The data used for the analysis were obtained from the China Agricultural Statistical Yearbook, the China Agricultural Products Import and Export Monthly Statistical Report, the China Environmental Yearbook, and the EPS Global Statistics Platform. Per capita income of farmers and the amount of investment in environmental pollution control was converted to constant 2002 prices. The amount of foreign trade in agricultural products and the amount of foreign direct investment in agriculture were converted to 2002 constant prices according to the average exchange rate of RMB in previous years. The descriptive statistical characteristics of the variables are shown in Table 5.

Table 5. Descriptive statistics of variables.

Variables	Abbreviation	Obs	Unit	Mean	Std.Dev	Min	Max
Agriculture Green TFP	GTFP	450	/	1.06	0.09	0.86	1.54
Scale of foreign trade	Trade	450	RMB 10 thousand Yuan	2,423,533	3,826,027	3543.08	25,892,799
Foreign direct investment	FDI	450	RMB 10 thousand Yuan	3,910,778	4,747,961	74,750.55	30,408,194
Technology inputs	T	450	people	22,350.74	12,104.09	2186	56,991
Human capital	HC	450	year	8.59	0.97	6.08	12.12
Rural income	Inc	450	RMB yuan	1471.26	1131.93	65.50	5409.56
Environmental regulation	Er	450	RMB 100 million Yuan	162.62	171.20	1.1	1281.9
Industry structure	Str	450	/	31.44	9.09	13.80	58.02

Natural logarithms were taken for all variables to eliminate heteroskedasticity and to maintain consistency with the econometric model. In addition, in order to avoid "pseudo-regression", all variables were logged and subjected to unit root LLC test, Breitung t-stat test, IPS test, ADF test, and PP test, and the results are shown in Table 6.

Table 6. Panel data stability tests.

Variables		Levin, Lin & Chut	Breitung t-Stat	Im, Pesaran and Shin W-Stat	ADF-Fisher Chi-Square	PP-Fisher Chi-Square
GTFP	Log-Level	−17.59 ***	−11.16 ***	−11.93 ***	232.28 ***	344.93 ***
	First difference	−26.54 ***	−11.93 ***	−18.89 ***	351.33 ***	551.25 ***
Trade	Log-Level	−7.39 ***	0.34	−2.89 ***	110.26 ***	139.97 ***
	First difference	−22.29 ***	−8.28 ***	−14.09 ***	255.74 ***	302.50 ***
FDI	Log-Level	−3.80 ***	1.84	−1.91 **	113.56 ***	85.28 **
	First difference	−19.72 ***	−1.10 ***	−12.54 ***	226.47 ***	258.29 ***
T	Log-Level	−2.00 **	−4.33 ***	0.56	79.73 **	97.19 **
	First difference	−19.22 ***	−8.58 ***	−11.86 ***	231.37 ***	311.33 ***
HC	Log-Level	−9.14 ***	−2.61 ***	−5.46 ***	129.70 **	102.87 ***
	First difference	−16.67 ***	−9.49 ***	−11.01 ***	215.75 ***	306.40 ***
Inc	Log-Level	−6.86 ***	−7.98 ***	−4.71 ***	107.37 ***	107.45 ***
	First difference	−23.29 ***	−24.16 ***	−18.04 ***	322.11 ***	412.66 ***
Er	Log-Level	−10.82 ***	−8.06 ***	−6.31 ***	135.69 ***	142.10 ***
	First difference	−16.75 ***	−11.38 ***	−14.20 ***	259.87 ***	339.37 **
Str	Log-Level	−7.62 ***	2.56	−3.20 ***	108.81 ***	168.63 ***
	First difference	−18.09 ***	−4.99 ***	−12.47 ***	243.39 ***	332.46 ***

Note: ***, ** are significant at the 1% and 5% levels, respectively; values in parentheses indicate standard errors.

The unit root and cointegration tests of the variables are shown in Table 6, and the first-order differences of all variables are significant at the 10% level, indicating that the panel data are stationary in general.

4.3. Empirical Testing and Analysis

Since all changes in economic factors have a certain inertia, the current behavior of individuals often depends on their past behavior patterns, and the change and improvement of agricultural green TFP is a continuous dynamic process. Therefore, this paper constructs a dynamic panel model and introduces a lagged variable of green TFP to obtain more effective estimation results, adopting the generalized method of moments (GMM) estimation method to verify the result. The systematic GMM model and differential GMM model were used to analyze the factors influencing agricultural productivity in China from the perspective of environmental constraints, and the results are shown in Table 7. All variables in Table 7 are taken as logarithms.

Table 7. Empirical results on the influencing factors of agricultural green TFP.

Variables	Differential GMM	System GMM
	(1)	(2)
GTFP(−1)	0.983 ***	0.775 ***
	(0.051)	(0.045)
Trade	0.081 ***	0.084 ***
	(0.012)	(0.015)
FDI	−0.098 ***	−0.028 ***
	(0.057)	(0.010)
HC	1.243 **	0.064
	(0.271)	(0.054)
T	−0.054 **	−0.117 ***
	(0.018)	(0.022)
Inc	−0.069	−0.014
	(0.024)	(0.025)
Er	−0.080 **	−0.047 ***
	(0.372)	(0.049)
Er^2	0.010 ***	0.008 *
	(0.003)	(0.005)
Str	−0.181 ***	−0.001
	(0.031)	(0.030)
AR1	0.002	0.001
AR2	0.586	0.101
Sargan	1.000	1.000
Constant term	1.440 ***	0.846 ***
	(0.339)	(0.394)
Obs	420	420

Note: ***, **, * significant at the 1%, 5%, and 10% levels, respectively; values in parentheses indicate standard errors.

According to the estimation results of the differential GMM model and the systematic GMM model for the dynamic panel, the Sargan test value is 1, so the original hypothesis of "all instrumental variables are valid" cannot be rejected. The AR(1) and AR(2) tests for the differential GMM are 0.002 and 0.586, respectively, and the AR(1) and AR(2) tests for the systematic GMM are 0.001 and 0.101, respectively, indicating that there is no first- or second-order autocorrelation in the difference of the disturbance terms. This shows that the dynamic panel model setting is reasonable.

From the regression results, it is clear that the first-order lagged term of agricultural green TFP, international trade in agricultural products, foreign direct investment in agriculture, agricultural technology input, and environmental governance have significant effects on agricultural green TFP. The effects of agricultural human capital and agricultural industry structure on agricultural green TFP are uncertain across models, while there is no significant effect of rural affluence on agricultural green TFP. Compared with the weak instrumental variability of the differential GMM, the results of the systematic GMM are more robust and were analyzed as follows.

For every 1% increase in agricultural green TFP in the previous period, agricultural green TFP increased by 0.78%. This indicates that the effect of agricultural green TFP in the previous period on agricultural green TFP in the current period is significant, which is in line with the reality. Agricultural productivity growth is influenced by production inputs and technological advances in the previous period, whereas in agricultural production, some factors, such as costs and prior-period emissions, have a persistent impact on the later period. Thus, the growth of green TFP in agriculture is also dynamic process.

International trade in agricultural products increases agricultural green TFP. Every 1% increase in the scale of agricultural trade increases agricultural green TFP by 0.08%. The demonstration effect, scale effect, learning effect, and industry chain effect of agricultural trade are stronger than the market and resource-crowding effects, driving the improvement of green TFP in agriculture. Chinese agricultural exports are repeatedly restricted by the green barriers of developed countries, which will force Chinese agriculture to change the current development model, improve the level of green agricultural development, and promote the application of agricultural technology. The import of agricultural products can also stimulate local competitors to imitate advanced technology. Imported agricultural products containing advanced cultivation methods and management experience produce a demonstration effect on domestic producers. The pressure of import-induced international market competition can also motivate domestic producers to learn and innovate, which is conducive to the development of domestic agriculture. However, we did not investigate how specific exports and imports in international trade of agricultural products affect agricultural green TFP, which should be addressed in future studies.

Agricultural FDI suppresses agricultural green TFP. For every 1% increase in agricultural FDI, agricultural green TFP decreases by 0.03%. Since the reform and opening up, the Chinese government has been encouraging foreign direct investment in the agricultural sector, with a view to injecting new vitality into agriculture and spreading advanced technology, production methods, and management concepts. It has been argued that FDI can raise the technological level of the host country and boost productivity growth under the condition that the spillover channel is open. However, most agricultural FDI enterprises invest and establish production bases in terms of China's location advantages, abundant agricultural resources, and cheap labor. Due to the difficulty of productizing agricultural technologies and the inadequate intellectual property rights system in China, few agricultural FDI enterprises have taken the initiative to transfer their production technologies. Some transferred production technologies also run the risk of not matching the local market reality. At present, the quality of China's agricultural labor force is generally low, and most agricultural producers find it difficult to imitate advanced technologies and production methods. In addition, foreign direct-investment enterprises, on the one hand, squeeze the market share and cause the "crowding-out effect" due to the brain drain of local enterprises, and on the other hand, the expansion of production scale and resource consumption slows down the pace of agricultural green transformation, aggravates agricultural surface pollution, and inhibits the growth of agricultural green TFP.

Agricultural technology inputs are not conducive to the growth of green TFP in agriculture. For every 1% increase in agricultural technology inputs, agricultural green TFP decreases by 0.12%. This shows that although China currently attaches some importance to agricultural technology inputs and invests a lot of human and material resources, there are problems, such as unreasonable input structure. The application of technology serves to increase production and income but fails to pay attention to the coordinated development of economic growth and environmental protection. The use of pesticides, fertilizers, and agricultural films drives productivity growth at a huge cost to the environment. However, due to data limitations, we were only able to use agricultural R&D personnel as a variable to measure agricultural technology inputs, which may affect the presentation of the final results; multiple perspectives may be needed to measure the robustness of the present findings in future studies.

The primary term of environmental regulation has a significant negative effect on agricultural green TFP, and the secondary term has a significant positive effect on agricultural green TFP. The negative effect of environmental regulation on green TFP in Chinese agriculture shows that the "cost-of-compliance" effect of environmental regulation on green TFP in Chinese agriculture at the early stage is greater than the "innovation-compensation" effect, which indicates that the government has invested a lot of financial and material resources in order to protect the environment, although the effect of environmental regulations is small and has not yet offset the negative impact of governance costs. However, a promising phenomenon is that the squared term of environmental regulation drives the growth of green TFP in agriculture, suggesting that the "innovation-compensation" effect increases at a faster rate after crossing an inflection point. Specifically, the increase in the intensity of environmental regulations makes agricultural producers reflect on their own problems of low factor utilization and high pollution emissions in the production process, prompting them to adopt new production technologies to optimize factor allocation, reduce pollution emissions, and increase the value added of their products [40]. The optimization of factor allocation efficiency can improve agricultural production efficiency, and the increase in competitiveness due to higher-value-added products can also enable agricultural producers to earn excess profits in the short term, offsetting the negative impact of higher environmental management costs [41]. In addition, with the government's increasing attention to environmental protection issues, green finance subsidies are being introduced, which will reduce the R&D costs of clean technologies and financing costs for agricultural producers and promote the efficiency of environmental management. The environmental regulation introduced by the Chinese government have been encouraging research, development, and applications of green agricultural production technologies while preventing and controlling agricultural surface pollution. The concept of green development has been deeply rooted in the hearts of the public. The market competitiveness of green agricultural products is increasing, and the "innovative-compensation" effect of environmental regulation will become increasingly apparent.

5. Conclusions and Policy Implications

We measured agricultural productivity under the environmental-constraint perspective using the SBM-ML index method based on provincial panel data from 2002 to 2016, with agricultural surface source pollution as the non-desired output. A dynamic panel regression model was used to empirically analyze the factors influencing agricultural productivity to provide a reference for formulating policies to alleviate the conflict between economic development and environmental pollution. The main conclusions drawn from the empirical analysis are as follows.

China's agricultural green TFP shows a trend of slow incremental growth year by year. The growth of agricultural green TFP mainly comes from the increase in the green technologic progress rate. In terms of geographic disparity, agricultural green TFP in the eastern, central, and western showed a high-to-low gradient. The agricultural green TFP showed a significant positive spatial correlation in some years. As for the influencing factors, the expansion of foreign trade in agricultural products is beneficial to enhance agricultural green TFP, whereas foreign direct investment in agriculture and agricultural technology input inhibits the growth of agricultural green TFP. There is a significant U-shaped relationship between environmental management inputs and agricultural green TFP.

Based on the above and empirical results, Chinese agriculture is seeking a sustainable development path with high yield and low resource consumption. To improve the development of green agriculture and reduce regional differences, the driving factors need to be taken into account to come up with corresponding policies.

First, because agricultural trade is the main contributor to agricultural GTFP growth across China, the government should vigorously develop modern trade modes with less environmental pollution, high added value, and low resource consumption. On the one hand, export agricultural products should be distinguished as either clean agricultural products or pollution-intensive agricultural products according to the degree of resource consumption and pollution in the production process. On the other hand, efforts should be made to achieve "moderate imports". The structure of imported agricultural products should be optimized, and inspection and quarantine should be strengthened for imported agricultural products from epidemic areas.

Second, policy makers could implement selectively high-quality green foreign investment projects. It is essential to establish an ecological early-warning system to monitor and control agricultural surface source pollution emissions. Technology spillover channels should be unblocked to absorb the advanced technology brought by foreign investment projects.

Third, policy makers could consider improving R&D efficiency through digital technologies. In the future, agricultural challenges such as climate change and natural resource degradation will require a shift from the past focus on productive technologies to digitally focused technological innovation. Artificial intelligence, Internet of Things, blockchain, and other technological applications will re-enable the agricultural industry. Various new technologies, such as sensors, drones, and robots, will be more widely used in agricultural production. The application of these new technologies will accelerate the digital transformation of all aspects of traditional agriculture, improve total factor productivity and release the amplification, superposition, and multiplication effects of digital technology on rural economic and social development. Favorable digital technology and human capital should be input in western and central areas to promote regional synergy development.

Finally, the government could consider increasing investment in special funds for agricultural pollution control and establish a financial support system linked to the reduction of agricultural pollutants. Special subsidies could also be provided to producers who promote and use soil-testing technology and clean production technologies. Agricultural subsidies should be transformed from direct subsidies of the fertilizer and pesticide industries to subsidies for agricultural producers, agricultural projects, and enterprises. Farmers should be encouraged to adopt environmentally friendly technologies, and the regulation of agricultural surface pollution should be transferred to individual conscious behavior.

6. Research Limitations and Future Directions

In accounting for agricultural surface source pollution, the unit-survey evaluation method was used to measure and analyze the characteristics and trends of pollution emissions from agricultural surface source pollution by combining the pollution production and discharge coefficients of each pollution unit. The survey mainly covered agricultural fertilizer, livestock and poultry breeding, agricultural solid waste, and rural household pollution. However, not all pollution-causing units were fully investigated, and due to data limitations, it was not possible to obtain dynamic changes in pollution production and discharge coefficients. The above factors may lead to bias in the accounting of agricultural surface source pollution emissions. In the future, the scope of production and discharge units of the unit-survey evaluation method can be further expanded, or more accurate production and discharge coefficients can be obtained through field research to obtain more accurate data on agricultural surface source pollution.

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Appendix A

Table A1. Green TFP and decomposition values in eastern provinces (2002–2016).

East	Green Technology Efficiency	Green Technologic Progress Rate	Pure Technical Efficiency	Scale Efficiency	Green TFP
Beijing	1.000	1.164	1.000	1.000	1.164
Zhejiang	0.981	1.110	0.980	1.000	1.089
Jiangsu	0.987	1.095	0.976	1.009	1.080
Shanghai	1.000	1.075	1.000	1.000	1.075
Fujian	0.970	1.106	0.968	1.000	1.073

Table A1. *Cont.*

East	Green Technology Efficiency	Green Technologic Progress Rate	Pure Technical Efficiency	Scale Efficiency	Green TFP
Shandong	0.968	1.092	0.966	1.000	1.057
Hebei	0.963	1.093	0.979	0.982	1.052
Guangxi	0.966	1.088	0.972	0.992	1.051
Guangdong	0.962	1.093	0.959	1.000	1.051
Tianjin	0.953	1.096	1.024	0.932	1.045
Liaoning	0.951	1.096	0.984	0.965	1.042
Hainan	0.916	1.103	0.978	0.936	1.011
Mean	0.960	1.097	0.978	0.982	1.055

Table A2. Green TFP and decomposition values in central provinces (2002–2016).

Central	Green Technology Efficiency	Green Technological Progress Rate	Pure Technical Efficiency	Scale Efficiency	Green TFP
Shanxi	0.977	1.093	1.007	0.968	1.067
Hubei	0.968	1.091	1.001	0.965	1.056
Hunan	0.967	1.090	0.998	0.967	1.054
Anhui	0.964	1.091	0.987	0.974	1.051
Heilongjiang	0.952	1.101	0.981	0.969	1.048
Jiangxi	0.952	1.091	0.977	0.972	1.038
Henan	0.951	1.088	0.950	1.001	1.034
Jilin	0.933	1.091	0.955	0.975	1.018
Inner Mongolia	0.926	1.098	0.953	0.969	1.017
Mean	0.963	1.094	0.985	0.975	1.053

Table A3. Green TFP and decomposition values in western provinces (2002–2016).

West	Green Technology Efficiency	Green Technological Progress Rate	Pure Technical Efficiency	Scale Efficiency	Green TFP
Guizhou	0.961	1.090	0.993	0.965	1.049
Shaanxi	0.964	1.090	0.995	0.967	1.051
Qinghai	0.980	1.091	1.022	0.956	1.069
Sichuan	0.937	1.091	0.963	0.971	1.022
Xinjiang	0.967	1.088	0.996	0.968	1.052
Gansu	0.955	1.095	0.986	0.966	1.046
Chongqing	0.976	1.085	1.000	0.974	1.058
Ningxia	0.957	1.090	0.875	1.102	1.043
Yunnan	0.928	1.094	0.956	0.968	1.015
Mean	0.958	1.091	0.975	0.981	1.045

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