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Agricultural Ecological Efficiency under the Carbon Emissions Trading System in China: A Spatial Difference-in-Difference Approach

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Abstract: The agriculture sector plays a significant role in the development of the national economy and providing raw materials to the industrial sector. Trying to get more agricultural productivity, most farmers ignored the adverse effects of agricultural chemicals or pesticides that have a negative impact on the environment. So, the importance of agricultural ecological efficiency needs to be understood. This study attempts to explore whether agriculture, as an important source of carbon dioxide production, can have an effective impact on the agricultural ecological efficiency of carbon trading pilot policies in the context of the global implementation of carbon trading. This study evaluated the agricultural ecological efficiency (AEE) and its spatial distribution characteristics of 31 provinces in China, the data period was from 2000 to 2018. By applying the spatial difference-in-difference (SDID) approach, the study investigates the effects of low-carbon policies on agricultural ecological efficiency in pilot areas. The results demonstrate that low-carbon trading pilot policies have a significant impact on agricultural ecological efficiency. At the same time, the effects of regional economic development, population growth, urbanization, and urban innovation on efficiency are also significant. The improvement of agricultural ecological efficiency requires not only the full implementation of low-carbon trading pilot policies but also the development of regional economy and high-quality agriculture. The findings provide further policy recommendations for high-quality agricultural development.



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Keywords: agricultural ecological efficiency; non-expected output model; spatial difference-in-difference model; carbon emission trading

1. Introduction

The production model based on “petroleum agriculture” has greatly promoted agricultural production. But the cumulative effect of “reverse ecological” is also increasingly evident [1]. Data from “the Second National Pollution Source Census Bulletin” show that in 2017, the chemical oxygen demand (COD), total nitrogen (TN), and total phosphorus (TP) caused pollution generated in China’s agriculture that accounted for 49.77%, 46.52%, and 67.21% of the corresponding pollution, respectively. Chemicals, wastes in agriculture, sewage, and garbage generated in daily life, are the main causes of agricultural pollution [2]. Therefore, sustainable agriculture must analyze the problems in agricultural production. Also, the contradiction between agricultural production and ecology must be alleviated. The ecological efficiency proposed by Schaltegger and Stum in 1990 has gradually become an important analytical tool for measuring sustainable development [3]. Further,

urbanization and the integration of agriculture and tourism have an impact on agricultural ecological efficiency [4,5].

At present, many methods are used to evaluate the ecological efficiency of agriculture (AEE), including ratio method, ecological footprint analysis, life cycle, stochastic frontier analysis, energy analysis, and data envelopment analysis (DEA), each with its strengths and weaknesses [6]. Among them, DEA is the most used method to evaluate the AEE because of its strong objectivity, simplicity, and comprehensiveness. The evaluation of agricultural ecological efficiency (AEE) has attracted widespread attention. These studies have mainly measured the AEE of rice, tea, corn, and other crops [7–9]. The driving factors, regional differences, temporal and spatial characteristics that have evaluated China’s agricultural ecological efficiency have been discussed at the national level [10–16]. There have also been many studies analyzing data from prefecture-level cities and counties [17–22]. However, the aforementioned studies have different conclusions due to different indicators and models.

In general, the existing studies have been instructive concerning the measurement of agriculture ecological efficiency (AEE), the description of AEE’s spatial and temporal evolution, but they have not widely discussed the impact of AEE on economic development. By way of addressing this gap, this study uses the data of 31 provinces in China from 2000 to 2018 to estimate the AEE and its spatial distribution characteristics. The Super-Slack Based Measure of non-expected output has been used to empirically analyze the generalized agriculture. Taking the dual factors of agricultural carbon emissions and pollution as non-expected output. Based on this, the impacts of carbon emissions trading pilots on economic growth are researched using the spatial difference-in-difference method (SDID), and one of spatial X Lag (SLX) model, the spatial autoregressive (SAR) model, the spatial error model (SEM), the spatial Durbin model (SDM), the spatial Durbin error model (SDEM) and the spatial autocorrelation (SAC) model was selected for Wald test and LR test.

2. Materials and Methods

2.1. Data Description

Agriculture ecological efficiency is the ratio of output to input. The input and output indicators in the non-expected output SBM model to measure AEE are used to measure the agricultural ecological efficiency (AEE). Production factors that can produce economic value usually serve as input indicators, while economic output, as well as the non-expected output, such as environmental pollution, often serve as output indicators. However, there is a lack of further research because COD, TN, and TP are mostly integrated into agricultural non-point source pollution by existing research. Therefore, considering the representativeness of agricultural input and output, as well as the availability and accuracy of data, the indicator system is constructed from three aspects: agricultural resource consumption, agricultural expected output, and non-expected output (Table 1).

Table 1. Indicators of Agricultural AEE Input Expected Output and Non-Expected Output.

Indicators	Variables	Variable Description
Input	Labor	Number of employees in the primary industry (ten thousand people)
	Machinery input	Total power of agricultural machinery (ten thousand kilowatts)
	Water input	Irrigation area (thousand hectares)
	Land input	The total sown area of crops (thousand hectares)
	Fertilizer input	Fertilizer application amount (ten thousand tons)
Expected output	Agricultural economic growth	Total agricultural output value (price in 2000, 100 million yuan)
Non-expected output	Pollutant emission	COD (ten thousand tons)
		TN (ten thousand tons)
	Carbon emission	Carbon dioxide (CO ₂) emissions (ten thousand tons)

As for the key explanatory variable, this thesis adopted AEE estimated by the SBM-undesirable model. By referring to the prior literature, several control variables were

employed: (1) economic development (lnpgdp), which was calculated by the logarithm of the provincial GDP per capita; (2) urbanization (uL), which was calculated by the direct ratio of the population of each city to the total population of the region; (3) innovation investment (lnRD), which was calculated by the logarithm of the investment of financial funds in science and technology; and (4) population size (lnpeople), which was calculated by the logarithm of the total population of the region [23,24]. Regarded as a “quasi-natural experiment”, the CET pilot was mainly launched in 2013. Therefore, only 2013 and later are recognized as pilot years, Beijing, Tianjin, Shanghai, Chongqing, Guangdong, Hubei (Shenzhen is not considered due to the low level of agricultural development), and the other 25 provinces are the control group.

Data Sources

Provincial-level data on outputs and inputs, which operate on the SBM-undesirable model, were collected from the China Statistical Yearbook, China Agriculture Yearbook, China Rural Statistical Yearbook, China Land and Resources Yearbook, China Energy Statistical Yearbook, China Environment Statistical Yearbook, and provincial statistical yearbooks (all the above can be found in <http://www.stats.gov.cn/tjsj/ndsj/>, accessed on 11 April 2021) over the years, and compiled the panel data sets of 31 provinces and cities in Mainland China (except Hong Kong, Taiwan, and Macau) from 2000 to 2018.

2.2. Model Specification

2.2.1. The SBM of Non-Expected Output

The SBM model of non-expected output was conducted to measure AEE [25] built the SBM-Undesirable model in 2003 by bringing in expected output and non-expected output, which effectively solved the traditional DEA's problems of inefficiency index adjustment and environmental negative externalities. The basic principles of the SBM-Undesirable model are as follows:

Assuming that a decision-making unit in agricultural production is composed of an input vector and two output vectors (including expected output and non-expected output), there are a total of n decision-making units (DMU), including m types of input elements, $q1$ types of expected output, and $q2$ types of non-expected output. Defining the matrices X , Y , and Z to be $X = [x_{ij}] = [x_i, \dots, x_n] \in R^{m \times k}$, $Y = [y_{ij}] = [y_i, \dots, y_n] \in R^{q1 \times k}$, $Z = [z_{ij}] = [z_i, \dots, z_n] \in R^{q2 \times k}$ respectively, then under constant returns to scale, the production possibility is set. The SBM-undesirable model is model (1) (Wang et al., 2018; Feng et al., 2019, [26]):

$$\begin{aligned}
 P(x) &= \{(x, y, z) | x \geq X\lambda, y \leq Y\lambda, z \geq Z\lambda, \lambda \geq 0\} \\
 \rho_j^* &= \min \frac{1 - \frac{1}{m} \sum_{i=1}^m \frac{S_{ij}^-}{x_{ij}}}{1 + \frac{1}{q1+q2} \left(\sum_{r=1}^{q1} \frac{S_{rj}^y}{y_{rj}} + \sum_{h=1}^{q2} \frac{S_{hj}^z}{z_{hj}} \right)} \\
 \text{s.t. } x_j &= X\lambda + S_j^-, y_j = Y\lambda - S_j^y, z_j = Z\lambda + S_j^z \\
 S_j^- &\geq 0, S_j^y \geq 0, S_j^z \geq 0, \lambda \geq 0
 \end{aligned} \tag{1}$$

where λ denotes the weight vector; S_j^-, S_j^y, S_j^z denotes slack variables, which respectively represent the input redundancy, expected output insufficient, and non-expected output redundancy of DMU j ; ρ^* denotes the ecological efficiency of the DMU. When $\rho^* < 1$, DMU is in an efficiency loss state, which can be transferred into an effective state by further optimization of input or output. Otherwise, when $\rho^* = 1$, DMU is in a relatively effective state and $S_j^- = S_j^y = S_j^z = 0$ at this time.

The above model is a nonlinear programming model, which can be transformed into a linear programming model through the following [27] transformation:

$$[\text{Un - Outputs SBM}'] \tau^* = \min t - \frac{1}{m} \sum_{i=1}^m \frac{S_{ij}^-}{x_{ij}}$$

Subject to

$$\begin{aligned} 1 &= t + \frac{1}{q1 + q2} \left(\sum_{r=1}^{q1} \frac{S_{rj}^y}{y_{rj}} + \sum_{h=1}^{q2} \frac{S_{hj}^z}{y_{hj}} \right) \\ x_j t &= X\Lambda + S_j^-, y_j = Y\Lambda - S_j^y, z_j = Z\Lambda + S_j^z \\ S_j^- &\geq 0, S_j^y \geq 0, S_j^z \geq 0, \Lambda \geq 0, t > 0. \end{aligned} \quad (2)$$

When this model is based on constant returns to scale, the SBM-undesirable model with variable returns to scale can be constructed by adding the constraint $\sum_{i=1}^m \lambda_i = 1$ into the model. Further, modifying the input or output constraints can also construct an output or input-oriented SBM-undesirable model. In this study, only Model 1 is used to estimate AEE, and other cases are not considered.

2.2.2. Difference-in Difference (DID) Model

Both the single difference method and DID method can be used to test whether there is an impact before and after the implementation of the policy, but the DID method is applied more because it can effectively alleviate the endogenous problem in measurement. Therefore, the study adopts the DID method to evaluate the impacts of China's CET pilot policy on the regional AEE [28], which is constructed as follows:

$$AEE_{it} = \alpha_0 + \alpha_1 \times (\text{pilot}_i \times \text{post}_t) + \sum \alpha_j X_{it} + \lambda_i + \gamma_t + \mu_{it} \quad (3)$$

where AEE_{it} denotes AEE in the city i at year t ; α_0, α_1 denote constants; λ_i and γ_t denote individual fixed effects and time fixed effects, respectively; μ_{it} denotes the random error, which obeys the normal distribution; pilot_i denotes the dummy variable of CET pilot, which equals to 1 if it is a pilot province, otherwise 0; post_t denotes the time dummy variable of the pilot policy implementation, which equals to 1 after implemented ($t \geq 2013$ when the policy was implemented), otherwise 0; X_{it} denotes the control variables of AEE.

2.2.3. The Spatial Durbin Model (SDM)

The study used the provincial-level data to examine the impact of CET pilot policy on AEE and the spatial spillover effects by using a generalized spatial Durbin model. The model is set as follows:

$$AEE_{it} = \alpha + \rho(W \times AEE_{it}) + \beta \times DID_{it} + \sigma(W \times DID_{it}) + \omega \times Z_{it} + \lambda_i + \gamma_t + \mu_{it} \quad (4)$$

where DID_{it} denotes a dummy variable, which equals to 1 if province i implements the carbon trading pilot policy in year t , otherwise 0; Z_{it} denotes control variables; α denotes constants; β and ω denote general regression coefficients; ρ denotes spatial autoregression coefficient; σ denotes spatial autocorrelation coefficient; W denotes spatial weight matrix. Two different matrices are used to measure the specific impact of CET pilot policies in regions, namely the adjacent spatial weight matrix (W_1) and the geographical distance weight matrix (W_2). Specifically, in W_1 , if the province i and j share common boundaries, $W_{ij} = 1$, otherwise $W_{ij} = 0$ (a); W_2 is constructed by the reciprocal of the square of the geographic distance measured by latitude and longitude between the capital cities of the two provinces ($W_{ij} = \begin{cases} \frac{1}{d^2}, & i \neq j \\ 0, & i = j \end{cases}$), and the two weights are both matrixed and unitized.

Table 3. Cont.

Region/Year	2010	2011	2012	2013	2014	2015	2016	2017	2018	Average
Jiangsu	0.700	0.666	0.683	0.616	0.605	0.560	0.536	0.500	0.672	0.729
Zhejiang	1.000	0.742	0.811	0.608	0.598	0.550	0.514	0.442	0.636	0.780
Anhui	0.490	0.497	0.504	0.504	0.497	0.490	0.472	0.457	0.508	0.496
Fujian	0.777	0.748	0.763	0.707	0.702	0.667	0.660	0.751	0.796	0.782
Jiangxi	0.503	0.513	0.515	0.527	0.521	0.518	0.508	0.488	0.536	0.517
Shandong	0.571	0.564	0.575	0.552	0.549	0.533	0.526	0.500	0.561	0.584
Henan	0.570	0.566	0.576	0.549	0.546	0.529	0.523	0.496	0.564	0.568
Hubei	0.530	0.535	0.537	0.522	0.517	0.510	0.502	0.480	0.525	0.538
Hunan	0.540	0.545	0.549	0.529	0.525	0.517	0.506	0.484	0.523	0.533
Guangdong	1.000	1.000	1.000	0.710	0.694	0.660	0.673	0.706	0.716	0.903
Guangxi	0.557	0.560	0.570	0.539	0.540	0.521	0.513	0.489	0.561	0.545
Hainan	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Chongqing	0.604	0.608	0.616	0.584	0.590	0.562	0.560	0.535	0.612	0.585
Sichuan	0.556	0.558	0.563	0.545	0.542	0.526	0.523	0.501	0.553	0.556
Guizhou	0.505	0.496	0.512	0.524	0.523	0.510	0.507	0.487	0.550	0.536
Yunnan	0.551	0.551	0.557	0.537	0.536	0.521	0.512	0.492	0.559	0.545
Tibet	1.000	1.000	1.000	1.000	1.000	1.000	0.446	1.000	1.000	0.971
Shaanxi	0.579	0.593	0.601	0.564	0.574	0.546	0.543	0.518	0.602	0.556
Gansu	0.519	0.528	0.538	0.531	0.528	0.519	0.514	0.495	0.544	0.522
Qinghai	0.457	0.472	0.472	0.488	0.488	0.473	0.477	0.463	0.495	0.477
Ningxia	0.429	0.438	0.444	0.449	0.446	0.441	0.424	0.433	0.488	0.428
Xinjiang	0.533	0.535	0.540	0.537	0.527	0.518	0.504	0.489	0.540	0.532
National level	0.642	0.635	0.643	0.617	0.588	0.600	0.578	0.583	0.636	0.631
Central China	0.528	0.533	0.538	0.531	0.526	0.516	0.503	0.484	0.537	0.535
Eastern China	0.843	0.811	0.824	0.759	0.675	0.735	0.743	0.739	0.792	0.805
Western China	0.564	0.569	0.575	0.567	0.565	0.552	0.500	0.530	0.583	0.562

The above table results explained that the national average of agricultural eco-efficiency dropped from 0.708 in 2000 to 0.636 in 2018, showing an overall downward trend. From the perspective of time, most of the provinces and cities with higher AEE are located in eastern China, followed by the western region and the central region. Because of the relative economic development in the eastern region, it is speculated that the AEE may be related to the geographical location or the degree of economic development. On average, AEE in the eastern region (0.805) > western region (0.562) > central region (0.535). The reason for this gap may be that the eastern, central, and western regions have the same ranking as ecological efficiency in terms of development, technological advancement, and population density. Specifically, more refined agricultural production tends to develop in the east. So, compared with the economically underdeveloped central and western regions, the eastern unit pays less resources and produces less pollution. On the other hand, although the western region has the least developed of the three regions, its population density is much smaller than that of the eastern and central regions. This may lead to the positive impact of low input demand for land labor, fertilizer, and machinery, which can offset technical deficiencies.

Note: Due to the different ways of dividing, this study takes the provinces, cities, and administrative regions, excluding the provinces and cities under the jurisdiction of eastern and western China as the central region, namely Shanxi Province, Liaoning Province, Jilin Province, Heilongjiang Province, Jiangxi Province, Henan Province, Hubei Province, and Hunan Province.

Regarding the changing trend in above Figure 1, the evolution of China's AEE follows a W-shaped curve, which can be roughly divided into three stages: the decline was the fastest in the first period (2000–2004), stabilized in the second period (2005–2011), and finally fluctuated in the third period (2012–2018). The two main inflection points of this W-shaped curve are in 2004 and 2014. Most of the relatively high-efficiency areas of agricultural ecological efficiency have been in the eastern coastal provinces during the whole process.

Compared with the previous lax policy control and severe ecological damage. The state and local governments have increased the control of agricultural resources as well as environmental resources after 2004, which may have helped the steady rise of AEE after 2004. In detail, in 2005, plenary sessions of the Central Committee of the Communist Party of China (CCCPC) establish the ecological compensation mechanism for the first time, followed by the “Water Pollution Prevention and Control Law” (2008), “Policy on Pollution Prevention and Control Technology for Livestock and Poultry Breeding Industry” (2010) and “Law of Water and Soil Conservation” (2010). Furthermore, ecologicalization reached a climax when the “Regulations on Ecological Compensation” was established and included in the legislative plan in 2010. In 2013, the regional ecological compensation system was established by the plenary sessions of CCCPC to attract social capital into the market for ecological environmental protection. These control measures seem to have promoted the reversal of the decline in AEE across the country, and gradually narrowed the gap in AEE between regions. This is closely related to the emphasis on rural ecological protection and industrial transformation. The emphasis on protecting the ecological environment and the transformation and upgrading of industries may have promoted the improvement of AEE.

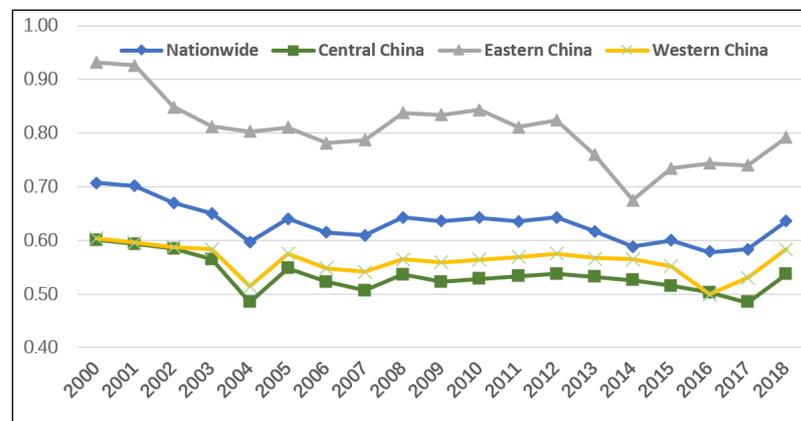


Figure 1. Changes in China’s Regional Agricultural Ecological Efficiency from 2000 to 2018.

Agglomeration Characteristics of AEE

Based on the u-shaped curve, the data of 2000, 2004, 2009, 2014, and 2018 were selected using Tebalau10.5 to investigate the spatial distribution of China’s agricultural ecological efficiency. In below Figure 2, the color changes from light blue to dark blue as its agricultural ecological efficiency (AEE) increases. The AEE value is divided into four levels, $<0, 0.4>$ is the fourth level, after increased by one level every 0.2, 1 is the highest value, and interval closed at the right. In 2000, 2009 regions including Shanghai, Beijing, Jiangsu, Hainan, and Tianjin were in the first level of AEE, and 8 regions, including Shandong, Liaoning, Henan, Sichuan, and Chongqing were in the second level, with the remaining 14 in the third level. By 2004, the number of the first level dropped to 7 as Tianjin has downgraded to the fourth level and Fujian to the second level. The number of the second level dropped sharply when the original members only retained the original Liaoning and the rest were downgraded. As a result, the number of third-level areas had increased significantly to 19, including the original second-level four regions, including Shandong, Hubei, and Hebei, as well as fourth-level Qinghai, while the fourth-level area had increased to three. In 2014, the first and second teams remained unchanged. Only Tianjin has left in the fourth level, and the rest were classified into the third-level area, making it expand to 23. In 2018, the distribution fluctuates. Tianjin jumped from the fourth level to the first level, the second level expanded to 7, and the remaining 19 regions merged into the third level. It is observed that there are large fluctuations in agricultural ecological efficiency (AEE) in some areas, represented by Tianjin, Fujian, and Qinghai, while the overall trend is stable.

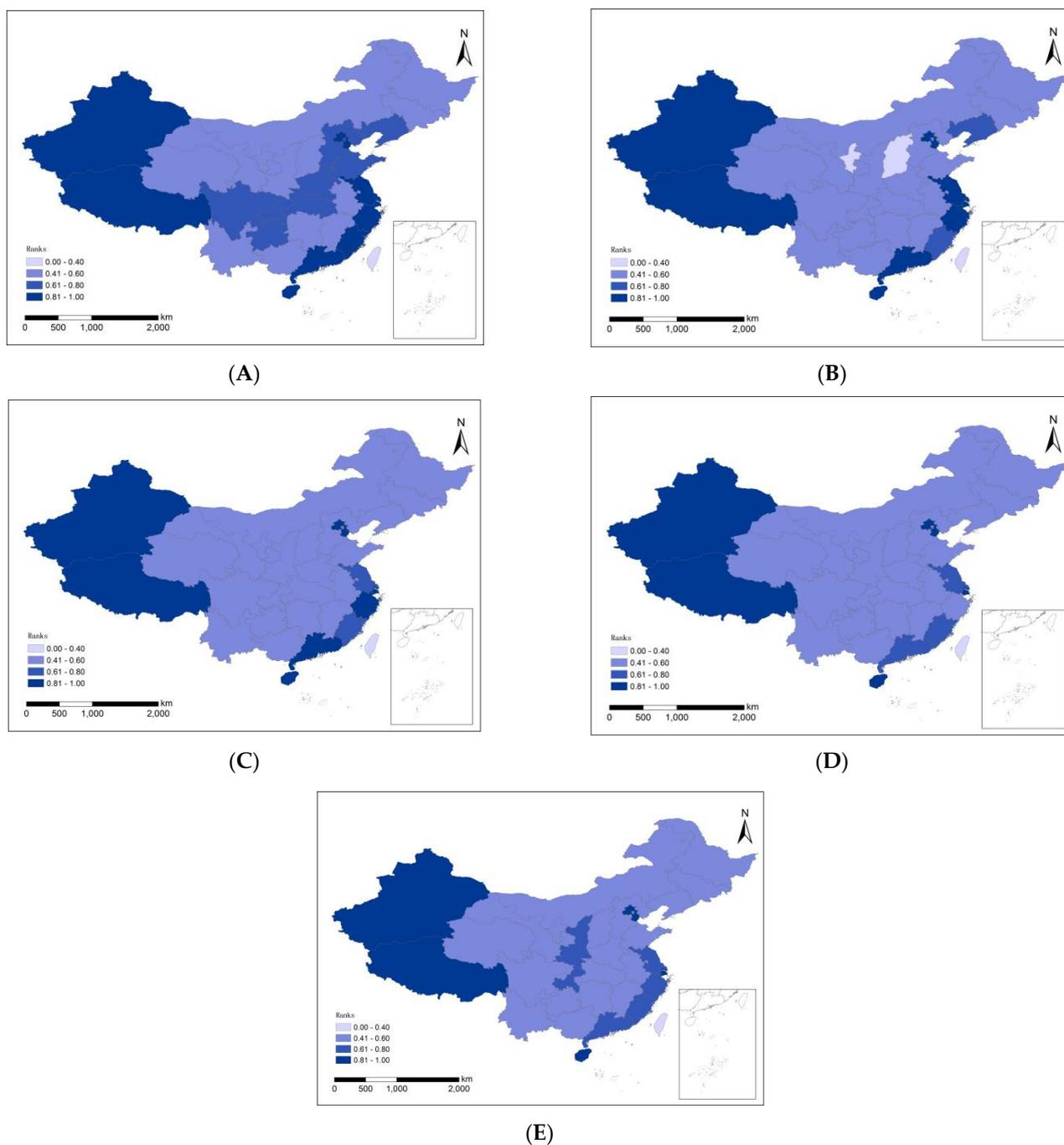


Figure 2. Distribution and Evolution of Regional Agricultural Eco—efficiency in China. (A) year 2000; (B) year 2004; (C) year 2009; (D) year 2014; (E) year 2018.

As shown in the above figure explained the most economically developed region in the country, the eastern part of China has the most regions in the first level of AEE. This result indicates that the distribution of China's AEE has a strong correlation with the level of economic development, which stabilized over time. That is to say, self-feedback optimization in developed regions, accompanied by positive externalities, supports positive impacts on the development of innovative advanced technologies and the improvement of AEE. Regarding the positive externalities, the “Notice on Carrying out the Pilot Work of Carbon Emissions Trading” was issued in 2011 and identified Beijing, Tianjin, Shanghai, Chongqing, Hubei, Guangdong, and Shenzhen as the pilots of CET. The carbon emissions as a non-expected output are indispensable for assessing AEE. Therefore, further study will

be implemented on the impact of the CET pilot on the SDID to tell whether active policies can play a supporting role in AEE and economic development.

3.2. Impact Assessment of CET Pilot Policy

3.2.1. Applicability Analysis of DID

Using data from 2000 to 2018, the Pearson correlation coefficient test results (Table 4) show that the national high-technology zone and the investment level of technological innovation input passed the 1% significance level, preliminarily proving the positive impact of the national high-tech zone.

Table 4. Correlation Coefficients Between Agricultural Eco-Efficiency and Various Variables.

	DID	lnpgdp	Urban	lnpeople	lnRD
Pearson	0.175 ***	0.264 ***	0.319 ***	−0.234 ***	0.0215 ***

Note: *** refers to 1% significant level, respectively.

In Figure 3, it can be seen that although there are differences in agricultural ecological efficiency, the changing trend is the same. That is, the difference between the experimental group and the control group is fixed, indicating that the two sets of data in this article meet the common trend test conditions. So, the DID model is applicable.

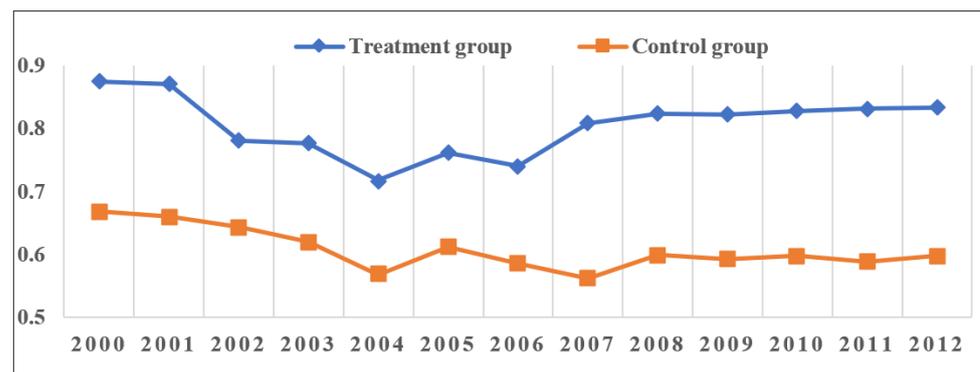


Figure 3. Common Trend Test of Agriculture Eco-Efficiency in Treatment and Control Groups.

This study further uses the regression method to test whether the agricultural (AEE) of the experimental group and the control group meets the common trend condition. Assuming that the pilot CET policy has been implemented from 2000 to 2012, the model is set as follows:

$$AEE_{it} = \alpha_0 + \alpha_1 \times piloted + \sum_{k=2000}^{2012} \delta_k \times post_k + \sum_{j=2000}^{2012} \psi_j \times post_j \times piloted + \mu_{it} \quad (5)$$

where $post \times piloted$ represents the cross term of the year dummy variable and the policy dummy variable. If the cross-term coefficient ψ_j is not jointly significant, there is no significant difference between the experimental group and the control group before the policy is implemented. The double-difference model has good applicability. The results show that $P(\psi_{2000} = \psi_{2001} = \dots = \psi_{2012} = 0)$, that is the original hypothesis of ψ_j being jointly 0 is accepted, and there is little difference between the two groups, which proves the applicability of the DID model again.

3.2.2. Analysis of Regression Results of DID Model

This study used the DID model to further test the effects of the pilot policy. To avoid the disturbance of cross-sectional synchronization and autocorrelation, this study follows Driscoll-Kraaythe, using the DKSE method to perform the DID model, and summarizes the final estimation results in Table 5.

Table 5. Coefficient Estimation Results of DID Model.

	(1)	(2)
DID	0.1481 *** (6.8640)	0.0696 ** (2.6719)
lnpgdp		0.0781 *** (3.0640)
urban		0.5874 *** (7.1142)
lnpeople		0.0343 *** (4.2961)
lnrd		−0.0704 *** (−13.9649)
_cons	0.6231 *** (39.6588)	−0.3996 (−1.6236)
Obs.	589	589
R-squared	0.0355	0.2036

Note: ***, ** refer to 1%, 5% significant level, respectively.

It is observed that the implementation of the CET pilot policy has significantly increased the agricultural ecological efficiency (AEE) (significant in 1% in Equation (1), and significant in 5% in Equation (2)). For the control variables, regional economic development has also improved the local agricultural ecological efficiency, with the coefficient of lnpgdp of 0.0781 (significant in the 1% level), while it was statistically beneficial for AEE to accelerate urbanization with the coefficient of urban of 0.5874. The coefficient of lnpeople was significantly positive, indicating that the dividend of population growth has contributed to the growth of AEE. The coefficient of lnrd was significantly negative, meaning that no statistical significance has been found for scientific and technological innovation input. The reason for the discrepancy may be that the use of R&D expenditure to measure scientific and technological innovation only reflects the level of innovation input. The lnrd coefficient is significantly negative, which means that the level of scientific and technological innovation input has not promoted the regional AEE. The reason for the discrepancy may be the incomplete measurement of scientific and technological innovation by the level of R&D expenditure.

3.3. Spatial Spillover Effect (SSE) Analysis

Spatial measurement models generally include the spatial X Lag (SLX) model, the spatial autoregressive (SAR) model, the spatial error model (SEM), the spatial Durbin model (SDM), the spatial Durbin error model (SDEM), and the spatial autocorrelation (SAC) model. First, the best measurement model was selected for accuracy, and through empirical analysis, SDM was finally employed. Under the spatial dependence of AEE, CET pilot policies have a positive impact on AEE (significant in the 1% level).

The SDID estimation results regarding the estimate for two spatial matrices are shown in Table 6. The influence direction and significance level of the variables in the two equations are not much different, indicating that the SDID model in this paper is not sensitive to the spatial matrix, thus proving the robustness of the model. Taking Equation (1) as an example, the spatial autocorrelation coefficient (0.054) has significance, illustrating the significant positive spatial autocorrelation of AEE. The use of traditional econometric models may lead to estimation errors due to ignoring the spatial effects of ecological efficiency. Meanwhile, the impact of regional economic development, population growth, urbanization, and technological innovation input on AEE have all been statistically significant.

Table 6. Regression Results of Spatial Durbin Model Under Two Weights.

Coefficients	The Adjacent Spatial Weight Matrix	The Geographical Distance Weight Matrix
Cons.	−2.989282 *** (−5.529862)	−5.444846 *** (−6.717390)
DID	0.054313 ** (2.056898)	0.065400 *** (2.551654)
lnpgdp	0.248871 *** (8.735223)	0.339614 *** (12.097246)
urban	−0.458767 *** (−4.247770)	−0.725269 *** (−6.654841)
lnpeople	−0.123263 *** (−6.413339)	−0.100042 *** (−5.129031)
lnRD	0.035486 *** (2.624192)	0.021388 * (1.594869)
W × DID	0.125443 *** (2.808217)	−0.054466 (−1.034768)
W × lnpgdp	−0.045147 (−0.924757)	0.012978 (0.180682)
W × urban	0.909285 *** (5.301019)	1.734884 *** (7.111946)
W × lnpeople	0.347690 *** (10.210177)	0.504328 *** (9.938163)
W × RD	−0.199200 *** (−7.946907)	−0.324300 *** (−7.749624)
rho	0.435505 *** (10.206927)	0.283881 *** (4.327892)

Note: ***, **, * refer to 1%, 5%, 10% significant level, respectively.

In the SDM, the coefficients of $W \times DID$, $W \times \lnpeople$, $W \times urban$, and $W \times RD$ were all significant, stating that there have been SSE in CET policies, population growth, urbanization, and urban innovation. Specifically, the implementation of CET pilot policies in adjacent regions had a positive spillover effect on AEE, and the coefficient of $W \times DID$ is significantly positive. In the same way, it can be seen that $W \times urban$ and $W \times \lnpeople$ have positive significance at the 1% level, that has the urbanization level and population level of neighboring areas may also promote agricultural ecological efficiency AEE, showing obvious positive SSE. However, the coefficient of $W \times RD$ is significantly negative, indicating the negative spillover effect of technological innovation in adjacent regions.

4. Conclusions and Recommendation

The agricultural ecological efficiency (AEE) dropped from 0.708 in 2000 to 0.636 in 2018, showing an overall downward trend, and the eastern region (0.805) > western region (0.562) > central region (0.535). Second, the CET pilot policy had a significant positive impact on agricultural ecological efficiency. Meanwhile, the effects of regional economic development, population growth, urbanization, and urban innovation on efficiency have also been significant. Finally, low-carbon trading pilot policies, population growth, urbanization, and urban innovation all have spatial spillover effects. The above research results show that the improvement of agricultural ecological efficiency requires not only the full implementation of low-carbon trading pilot policies but also the development of regional economy and high-quality agriculture. Therefore, this article proposes the following policy recommendations:

Establish an appropriate carbon emissions trading system from an overall perspective. In line with the overall ecological projection of the government, regional governments' decision-making should focus on carbon peaking and carbon neutrality, and establish a scientific carbon emission trading system. It is also essential to incentivize low-carbon technology innovation, which strengthens the SSE of innovation and reduces the cost of low-carbon agriculture. For example, strengthening carbon emission data collection and sorting capabilities improves the technology for collecting carbon emission data, and the latest big data technology can be used to establish a carbon emission database. In addition, the local area should activate market vitality and give full play to the independent regulation of the carbon trading market.

Develop rural economy and high-quality agriculture. Under the implementation of the rural revitalization strategy, the rural regional economy has a solid economic foundation for the improvement of agricultural ecological efficiency. Rural construction projects should be further performed to improve the rural living environment and attract labor to return to their hometowns for employment. More importantly, scientific research resources should be concentrated to advance clean agricultural production technologies and provide technical support for the improvement of agricultural ecological efficiency. In addition, policy decisions must be matched with the local area, that is, give full play to strengths and

make up for shortcomings, and provide further policy support for the improvement of agricultural ecological efficiency.

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