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The Impact of Agricultural Production Efficiency on Agricultural Carbon Emissions in China

Yong Zhu and Congjia Huo *

School of Business, Hunan University of Science and Technology (HNUST), Xiangtan 411201, China; zhuyong@mail.hnust.edu.cn
* Correspondence: huocongjia@mail.hnust.edu.cn

Abstract: With the rapid development of China's economy, China has become the world's largest carbon emitter. China not only has an obvious growth rate of industrial carbon emissions but also the intensity of agricultural carbon emissions is hovering at a high level. The development of China's agricultural economy has largely come at the expense of high emissions. Currently, under the background of global warming and difficulty in controlling greenhouse gas emissions, the development of low-carbon agriculture is an important way to realize the harmonious development of the ecological environment and economic growth and to promote the sustainable development of agriculture. The agricultural production efficiency is the main factor affecting the intensity of agricultural carbon emissions. Based on provincial panel data of China from 2010 to 2019, this paper establishes an indicator system and uses the super-efficiency SBM model to measure agricultural production efficiency. The regional agricultural carbon emissions were estimated using carbon-emission-related agricultural production activities. In order to study the nonlinear relationship between agricultural production efficiency and agricultural carbon emission intensity in the narrow sense, this paper uses a threshold regression model with agricultural carbon emissions as the threshold variable. Based on the analysis of China's agricultural production efficiency and agricultural carbon emissions from 2010 to 2019, an empirical test is conducted through a threshold regression model. The results show an "inverted U-shaped" relationship between agricultural production efficiency and agricultural carbon emission intensity. In areas with high agricultural production efficiency, the improvement of production efficiency can suppress the intensity of agricultural carbon emissions; in areas with low agricultural production efficiency, the improvement of production efficiency increases the intensity of agricultural carbon emissions. Finally, based on the research conclusions, this paper provides feasible suggestions and countermeasures for China's agricultural carbon emission reduction and improvement of agricultural production efficiency.

Keywords: agricultural production efficiency; agricultural carbon emission; super-efficiency SBM model; threshold effect; carbon emission reduction

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1. Introduction

With the rapid economic development, China has become a world leader in carbon emission. The World Resources Institute (WRI) published data on carbon dioxide emissions worldwide for the past 30 years. The top five economies regarding carbon dioxide emissions from 1990 to 2018 were China, the United States, the European Union, India, and Brazil. China surpassed the United States to become the world's largest carbon emitter around 2004. China tops the list with 7778 million tons of carbon dioxide emissions in 30 years. After entering the 21st century, the growth rate of carbon emissions in developed countries has been controlled, but the growth rate in China is obvious. Considering China's population size and economic development level, China's per capita carbon emission level is still lower than that of developed countries. However, global warming affects everyone's life. In 2015, governments worldwide held the 21st United Nations Climate Change Conference. Almost simultaneously, northern China experienced one of the worst air pollution in a decade. Sandstorms and smog caused a rapid shift in the attitude of Chinese residents towards the concept of environmental protection: from passive understanding and concern to active appeal and seeking solutions. In 2020, the Chinese government proposed at the 75th United Nations General Assembly: "China will increase its nationally determined contribution, adopt more powerful policies and measures, strive to peak carbon dioxide emissions by 2030, and achieve carbon neutrality by 2060".

Achieving carbon peaking and carbon neutrality requires the efforts of all aspects of China's society, economy, and residents. It also needs the coordinated development of agriculture, industry, manufacturing, and other industries, especially agricultural development. According to the "Initial National Communication on Climate Change of the People's Republic of China", the total emission of greenhouse gases in China in 1994 was 36.50×10^8 t CO_2 equivalent, of which carbon dioxide, methane, and nitrous oxide accounted for 73.05%, 19.73%, and 7.22%, respectively. Agricultural sources of greenhouse gas emissions account for 17% of China's total greenhouse gas emissions. According to the World Bank's WDI database, China's CH_4 and N emissions in 2005 reached 538 million t CO_2 equivalent and 567 million t CO_2 equivalent, of which agricultural sources accounted for 50% and 92.7% [1]. The research shows that, from 1991 to 2008, the CH_4 emission from the planting industry decreased from 999.50×10^4 t to 931.44×10^4 t, and the N_2O emission increased from 34.67×10^4 t to 48.74×10^4 t (Min J.S. and Hu H., 2012) [2]. From an international comparison point of view, China's CH_4 emissions are relatively close to those of the United States, and the trend of change is basically similar, but China's N_2O emissions are much larger than those of the United States (EPA, 2011) [3]. In 2019, China's carbon emissions were about 9.83 billion tons, and in 2020, China's carbon emissions were about 9.9 billion tons, a year-on-year increase of 0.71%. From the perspective of the main sources of carbon emissions in China, by 2020, China's carbon emissions will mainly come from thermal power generation, accounting for about 78%. Followed by industrial emissions (steel, cement, electrolytic aluminum), accounting for about 14%; agricultural emissions accounted for about 7% [4]. Before the 21st century, China's economic development was more dependent on agriculture, the industrial structure was extremely unreasonable, and the output value of the primary industry accounted for a relatively high proportion of the total output value. In addition, the low level of industrial development leads to low agricultural production efficiency, resulting in agricultural carbon emissions accounting for nearly 20% of China's total carbon emissions. With the Chinese government's emphasis on environmental quality and the upgrading of industrial structure, the level of green technology has improved, and the proportion of China's agricultural carbon emissions has gradually decreased. China is still in the process of industrialization and urbanization. China is still an unstable spatial structure of the population, and the contradiction between people and land is quite prominent. Agriculture is a disadvantaged sector with relatively low returns, and the phenomenon of agricultural economic development at the expense of high emissions has existed for a long time. Furthermore, food security is the top priority of a country. Food is an essential public good, and it is objectively necessary to ensure agricultural output. Based on the improvement of agricultural production efficiency, the ecological environment change in Chinese agricultural production has not been given due attention.

China is a big country producing and using chemical fertilizers and pesticides. Data from the National Bureau of Statistics of China show that in 2013, China's chemical fertilizer production volume was 70.37 million tons, and agricultural chemical fertilizer application volume was 59.12 million tons. In 2019, China's agricultural fertilizer input amounted to 57.2 million tons, and the application intensity reached 325 kg/hm^2. In 2020, the pure amount of agricultural chemical fertilizers in China reached 52.5065 million tons. The amount and intensity of agricultural chemical fertilizer application in China have declined in the last decade. Although chemical fertilizers have made a significant contribution to the increase in grain production, according to the "Action Plan for Zero Growth of Fertilizer

Use by 2020" issued by the Ministry of Agriculture of China, there are still four problems with applying chemical fertilizers in China. First, the average application amount per mu is high. The average amount of chemical fertilizer per mu of crops in China is much higher than the world average, 2.4 times that of the United States and 2.3 times that of the European Union. Second, the phenomenon of unbalanced fertilization is prominent. The economically developed areas in the east, the lower reaches of the Yangtze River, and the suburbs of cities have high fertilizer applications. Excessive fertilization of economic horticultural crops with high added value, such as vegetables and fruit trees, is more common. Third, the utilization rate of organic fertilizer resources is low. Fourth, the fertilization structure is unbalanced. Heavy chemical fertilizers, light organic fertilizers, heavy macronutrient fertilizers, light medium and trace element fertilizers, heavy nitrogen fertilizers, light phosphorus and potassium fertilizers, and "three heavy three light" problems are prominent. Although chemical fertilizers, pesticides, and agricultural film in China have decreased, it is still excessively applied compared to the international level. As a major agricultural producer, China needs to consider the negative impact of agricultural carbon emissions on the global climate while ensuring the output of farm products. The Ministry of Agriculture and Rural Affairs of China will strengthen initiatives to increase the utilization rate of chemical fertilizers and pesticides by another three percentage points by 2025 and promote the comprehensive green transformation of agricultural production methods. Therefore, it is of great significance to study the impact of agricultural production efficiency on agricultural carbon emissions in China. This is also conducive to the Chinese government optimizing fertilization and drug application patterns and integrating and promoting green prevention and control mode. It is also essential to build a green planting system and reduce the intensity of agricultural carbon emissions.

This paper selects the provincial-level data in China from 2010 to 2019 to measure agricultural production efficiency and agricultural carbon emissions and uses the threshold regression model to test the relationship between the two empirically. The rest of this article is organized as follows: Section 2 is a literature review of related topics; Section 3 measures the efficiency of agricultural production in Chinese regions using the super-efficiency SBM model and analyzes the time-evolution characteristics of agricultural production efficiency using kernel density estimation. Section 4 estimates the carbon emissions from agriculture in different regions of China. Its evolution characteristics were analyzed using Theil index and kernel density estimation, and its spatial distribution characteristics were analyzed using ArcMap software. Section 5 empirically tests the nonlinear relationship between agricultural production efficiency and agricultural carbon emission intensity in China using a threshold model. Section 6 presents the conclusions, policy recommendations, and future research directions of this paper.

2. Literature Review

2.1. Research on Agricultural Carbon Emissions

2.1.1. Calculation of Agricultural Carbon Emissions

Agricultural carbon emissions refer to the carbon dioxide emissions caused by the agricultural production process. Keith Paustian (Paustian et al., 1998) [5] believes that generalized agricultural carbon emissions are the main reason for the rise of carbon emissions in the economy. It is also estimated that agricultural carbon emissions account for about one-fifth of total carbon emissions. There are various sources of agricultural carbon emissions, different measurement methods, different research objects, and different estimation results. According to the origins of agricultural carbon emissions, there are three main ways to measure agricultural carbon emissions in current academic circles. First, agricultural carbon emissions are estimated from agricultural material consumption and waste disposal. Jane M.F. Johnson (2007) [6] believes that agricultural carbon emissions mainly come from the use and waste of input elements such as chemical fertilizers, pesticides, energy in agricultural production, the planting of rice fields in various periods, and the inappropriate burning and burial of crop straws. Tian W. et al. (2017) [7] used data on chemical fertilizers, pesticides, agricultural plastics, irrigation, and agricultural machinery to measure that carbon emissions from China's planting industry showed an inverted N-shaped pattern. Agricultural carbon emissions mainly come from central grain-producing provinces. Second, it is calculated based on methane, soil carbon dioxide, and nitrous oxide emissions from rice fields. The research of Leod (2010) [8] shows that the carbon emission of the crop industry mainly comes from changes in soil use and soil structure. Vleeshouwers and Verhagen (2002) [9] measured agricultural carbon emissions in a narrow sense based on factors such as crop characteristics, climatic conditions, and soil. Third, carbon emissions from animal husbandry and fishery production (Liu Lihui, 2015) [10]. Few scholars conducted the measurement of agricultural carbon emissions from this perspective. The object of this paper is the carbon emissions of the planting industry, which is not repeated here.

2.1.2. Influencing Factors of Agricultural Carbon Emissions

The primary purpose of measuring agricultural carbon emissions is to explore the influencing factors and find the agricultural carbon emission reduction pathway. Agricultural production activities have a long cycle, high dependence on natural climate, and many factors. The reasons for the formation of agricultural carbon emissions are complex, and the influencing factors are diverse. The academic community mainly studies the influencing factors of agricultural carbon emissions from two aspects. First, external factors such as carbon tax, innovation capacity, employment policy, etc., affect agricultural carbon emissions. Peter (2001) [11] concluded that carbon taxes had a negative impact on agricultural carbon emissions based on U.S. agricultural data in 1990 and 2020. Gerlagh (2007) [12] used an endogenous growth model to establish that technological progress can curb agricultural carbon emissions. Pamuk et al. (2014) [13] found that agricultural innovation capacity is also the primary influence on agricultural carbon emissions using the survey data from eight African countries. In addition, multiple policies such as employment policy, agricultural investment, and agricultural structural adjustment combine to influence agricultural carbon emissions (Lei, 2017) [14]. Second, internal factors, such as the impact of agricultural production methods on agricultural carbon emissions. The way of land production is the main factor leading to agricultural carbon emissions. Agricultural carbon emissions from less tillage, intensive tillage, and conventional tillage increased sequentially (Lal, 2004; Baumann, 2017) [15,16]. Gamboa and Galicia (2011) [17] also found that changes in land use can lead to changes in agricultural carbon emissions. Ji X.C. et al. (2019) [18] concluded that different intercropping methods produce additional crop carbon emissions by investigating the intercropping ways of corn and other crops.

2.2. Research on Agricultural Production Efficiency

Agriculture is the basis of national economic development, and accurate measurement of agricultural production efficiency is the basis for the study of sustainable agricultural development. The DEA model is mainly used to measure agricultural production efficiency in academia (Armagan, 2010) [19]. Battese (1995) [20] measured the productivity of 38 farms in India using a DEA model. Li Hangfei (2020) [21] also used the DEA model to calculate the agricultural production efficiency in different regions of China and found that the growth rates were ranked from high to low in the eastern region, the western region, and the central area. The measurement of agricultural production efficiency is mainly from two levels. First, the efficiency of agricultural production is measured from the national macro level. Farrell (1957) [22] was one of the first scholars to study agricultural production efficiency; he used the traditional DEA model to measure the efficiency of agricultural production in the U.K. Broekel and Boschma (2012) [23] studied the efficiency of the farm output in Germany. Second, the farm production efficiency is measured at the regional or inter-provincial level. Yu Yumin et al. (2018) [24] measured the agricultural production efficiency and found that it fluctuated around 0.84 using the data of Henan Province in China from 2001 to 2015. Pan. D et al. (2013) [25] used the SBM model to measure the agricultural production efficiency of 30 provinces in China and proposed improving agricultural production efficiency.

According to United Nations projections, there will be 4300 megacities with a population of more than 10 million by 2030, most of them in developing regions. In 2050, 68% of the world's population will live in urban areas. As the world urbanizes more rapidly, sustainable development increasingly depends on the successful management of urban growth. Comprehensive policies are needed not only to improve the lives of urban and rural residents but also to strengthen linkages between urban and rural areas. In this context, digital technology plays an important role in the field of precision agriculture (Trivelli et al., 2019) [26]. In addition, the distance-based hybrid localization algorithm has higher reliability and scalability in the agricultural field (Swain et al., 2021) [27], providing more paths for promoting agricultural productivity and reducing agricultural carbon emissions. The current academic research on the effect of agricultural production focuses on its measurement and influencing factors. Some scholars have also begun to consider the role of agricultural production efficiency in green agricultural production. The research of Li Bo (2011) [28] concluded that the labor force's scale, structure, and agricultural production efficiency have a suppressive effect on agricultural carbon emissions. However, there is still a lack of systematic research on the nonlinear relationship between agricultural production efficiency and agricultural carbon emissions. Therefore, the contributions of this paper are as follows: Based on previous research, the narrow agricultural production efficiency and agricultural carbon emission intensity were taken as the research objects. The super-efficiency SBM method was used to measure agricultural production efficiency, and carbon sources were used to estimate the carbon emissions of crop farming. Finally, this paper used the threshold regression model to empirically test the nonlinear relationship between the narrowly defined agricultural production efficiency and the carbon emission intensity of the planting sector.

3. Measurement and Dynamic Evolution of Agricultural Production Efficiency

3.1. Measurement Methodology (SBM) and Index System

3.1.1. Measurement Methodology

Accurate measurement of agricultural production efficiency in China is the basis for studying its relationship with agricultural carbon emission intensity. The measurement of agricultural production efficiency in the existing literature mainly focused on broad agriculture as the subject of study. However, the measurement of agricultural carbon emissions is based on the production activities of agriculture in a narrow sense. The broad sense of agricultural carbon emissions is dominated by the narrow sense of agricultural carbon emissions, so this paper takes the narrow sense of agriculture as the research object to measure production efficiency.

Data Envelope Analysis (DEA) is the most commonly used nonparametric frontier analysis method proposed by Charnel (1978) [29]. DEA methods mainly include CCR, BCC, and SBM models. Traditional DEA models cannot handle undesired outputs. Chung (1997) [30] proposed the Malmquist–Luenberger (ML) index based on the conventional DEA model to solve this problem. However, this radial-based ML index can only handle models where the desired output changes as much as the undesired output. When there is a non-zero slack between input and output, there is an overestimation error in the results measured by the ML index. In addition, the ML index must also choose a measurement perspective. Whether selecting the view of input or output, there will be a neglect of the other angle. SBM-DEA was proposed by Tone Kaoru (2001) [31]. Compared with the ML index, the SBM-DEA model also measures production efficiency from input and output. However, its results also include slack variables for the inefficiency measure with more minor errors. In order to more accurately measure the efficiency of agricultural production in each region of China, it is necessary to consider both output and input slack. Therefore, this paper took the province as the decision-making unit and used the Super Slacks-Based Measure (SBM) model to measure agricultural production efficiency.

There are 30 decision-making units (DMUs) in the super-efficiency SBM model. By considering the availability of data, four regions—Tibet, Hong Kong, Macau, and

Taiwan—were excluded from measuring agricultural productivity efficiency in Chinese provinces. There are seven types of inputs exit for agricultural production in each region, $X_n = \{X_1, X_2, \cdots X_7\} \in R^N$, and two types of output can be produced, $Y_m = \{Y_1, Y_2\} \in R^M$. The resulting non-radial SBM model, including input and output, is constructed as in Equation (1).

$$\rho* = \min \frac{1 - \left[\frac{1}{N}\sum_{n=1}^{N}\frac{S_n^x}{X_n^i}\right]}{1 + \frac{1}{M}\sum_{m=1}^{M}\frac{S_m^y}{Y_m^t}} \tag{1}$$

In Equation (1), S_n^x and S_m^y are input slack variables and output slack variables, respectively. The numerator and denominator of the objective function $\rho*$ calculated as the average distance between the actual input and output of the decision-making unit from the production frontier surface, respectively, which is the degree of inefficiency of input and output. The weight vector constraint of the decision unit is shown in Equation (2).

$$\sum_{j=1}^{I} Z_i^t = 1, Z_i^t \geq 0, S_n^x \geq 0, S_m^y \geq 0, i = 1, 2 \cdots I \tag{2}$$

The input and output constraint functions are s.t

$$\begin{cases} \sum\limits_{i=1}^{I} Z_i^t y_{i,m}^t - S_m^y = y_{i,m}^t, \ m = 1, 2 \\ \sum\limits_{i=1}^{I} Z_i^t x_{i,n}^t - S_n^x = x_{i,n}^t, \ n = 1, 2 \cdots 7 \end{cases} \tag{3}$$

Some results of super-efficiency SBM measurement exceed 1. When the objective function is $\rho \geq 1$, it means that the decision-making unit is effective. When the objective function is $0 \leq \rho < 1$, it means that there is an efficiency loss in the production of decision-making units, and the input and output need to be improved. The higher the value, the more efficient the agricultural production.

3.1.2. Indicator System and Data Sources

The measurement method of agricultural production efficiency is given above. The agricultural production efficiency in the narrow sense measures the utilization efficiency of the input resources by the planting industry. On the whole, the basis of production efficiency measurement is factor input and output. This paper takes the province as the decision-making unit to establish the agricultural production efficiency index system, as shown in Table 1.

Table 1. Index system of agricultural production efficiency.

Indicator Direction	Indicator Type	Specific Indicators (Units)	Calculation Method
input	Land	Agricultural sown area (thousand hectares)	Gross planted area of crops
	Finance	Financial support for agriculture expenditure (billion yuan)	Financial expenditure on agriculture, forestry, and water
	labor force	Number of agricultural laborers (10,000 people)	Number of people in primary industry × A
	Chemical fertilizer	Agricultural chemical fertilizer application amount (million tons)	Agricultural fertilizer input
	Mechanical	Agricultural mechanization (million kilowatts)	Total power of agricultural machinery
	Pesticides	Pesticide usage (million tons)	total agricultural use
	Agricultural film	Amount of Plastic film used (million tons)	Total use of agricultural plastic film
output	Output value	Agricultural output value (billion yuan)	Agricultural output value in agriculture, forestry, animal husbandry, and fishery sub-products
	Revenue	Per capita net income of agricultural production (yuan)	Per capita net income of rural households × A

Note: A = agricultural output value/total output value of agriculture, forestry, animal husbandry, and fishery.

In accordance with the existing literature, this paper selected the factors of land, finance, labor, fertilizer, machinery, pesticide, and agricultural film in agricultural production activities as input variables. Specifically from Table 1, the input variables mainly included the following: (1) Land input: expressed as the total sown area of crops. (2) Financial input: expressed by the financial expenditure of the regional government on agriculture, forestry, and water. (3) Labor input: There is no direct statistical data on the number of the labor force in agricultural production. This paper first calculated the proportion A of agricultural output value and the total output value of agriculture, forestry, animal husbandry, and fishery. Then, the labor input of agricultural production was estimated by multiplying the number of laborers in the primary industry and A. (4) The inputs of chemical fertilizers, machinery, agriculture, and agricultural film were expressed by the regional agricultural chemical fertilizer input, the total power of agricultural machinery, the full agricultural use, and the full use of agricultural plastic films, respectively. The output variables specifically include the following: (5) Output value: expressed as agricultural output value in the output value of agriculture, forestry, animal husbandry, and fishery sub-products. (6) Income output: there is currently no direct statistical caliber of planting income, so this paper takes the product of the per capita net income of rural households and A as the per capita net income of agricultural production.

The data of the agricultural production efficiency measurement index system are obtained from the "China Statistical Yearbook (Calendar Years)," "China Agricultural Statistical Yearbook (Calendar Years)," and the "Statistical Yearbooks (Calendar Years)" of each province. Due to the data availability, excluding the data of Tibet, Hong Kong, Macau, and Taiwan, a total of panel data of 30 areas in China from 2010 to 2019 were obtained. This paper used this to measure agricultural production efficiency.

3.2. Analysis of the Measurement Results of Agricultural Production Efficiency

This paper gave the measurement method and index system of agricultural production efficiency. Next, this paper measured the agricultural production efficiency of 30 provinces in China from 2010 to 2019. The measurement results are shown in Table 2.

It can be seen from Table 1 that there are two main characteristics of China's agricultural production efficiency from 2010 to 2019. First, the efficiency of agricultural production has steadily increased in most regions. The vast majority of provinces did not achieve effective agricultural production efficiency in 2010, except for Tianjin, Fujian, Guangdong, and other areas. China's agricultural production efficiency was 0.5345 in 2011. From the trend of provinces that have achieved effective agricultural production efficiency since then, agricultural production efficiency is more likely to be achieved due to policy inclination and environmental protection requirements. In general, Chinese agricultural production efficiency was low at that time. By 2014, there were five regions with rural production efficiency exceeding 1, including Beijing, Shanghai, Shaanxi, and other areas. During this period, Chinese agricultural production efficiency reached a small peak of 0.6024. Since then, the average value of agricultural productivity in China has declined. However, from 2010 to 2019, the volatility of agricultural production efficiency increased, and the number of regions that achieved agricultural production efficiency increased from less to more. By 2018 and 2019, the mean reached 0.6542 and 0.7814, respectively.

A total of 11 regions achieved effective agricultural productivity in 2019. The areas that perform effective production are mainly distributed in the developed areas along the eastern coast. The agricultural production efficiency of Shandong, Henan, Hunan, and other major grain-producing provinces is low. It is necessary to pay more attention to improving production efficiency following agricultural production. Second, there is a significant gap in agricultural production efficiency between regions. This gap has gradually narrowed as time has grown. In 2010, a total of 11 areas had agricultural productivity lower than 0.4. In 2016, four regions had agricultural productivity lower than 0.4. In 2019, only three regions had agricultural productivity below 0.4. Based on a slight increase in the average, the gaps in agricultural production efficiency between parts continue to narrow with the economic development of underdeveloped areas. The agricultural production efficiency in Gansu has been low, hovering around 0.3. Agricultural production efficiency increased significantly in Guizhou, Qinghai, Xinjiang, and other regions.

Table 2. The results of the measurement of agricultural production efficiency in different regions of China from 2010 to 2019.

Year	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
Beijing	0.657	0.7304	0.8042	0.8331	1.0062	0.8566	0.8566	0.8708	0.945	1.1366
Tianjin	1.0123	0.5769	0.6202	0.6616	0.7124	0.7734	0.8666	0.7992	0.9292	1.0868
Hebei	1.0001	1.0076	0.7406	0.636	0.5014	0.4784	0.4874	0.4458	0.5029	0.5594
Shanxi	0.2625	0.2782	0.2751	0.2986	0.3152	0.3048	0.3215	0.3119	0.3257	0.3593
Inner Mongolia	0.3754	0.416	0.4112	0.4305	0.4248	0.3907	0.3943	0.378	0.4255	0.4981
Liaoning	0.5285	0.6494	0.5818	0.5976	0.6219	0.6505	0.6286	0.5534	0.5901	0.6357
Jilin	0.3682	0.4266	0.4411	0.4538	0.4609	0.442	0.4012	0.3131	0.3481	0.3931
Heilongjiang	0.3448	0.4172	0.4671	0.5306	0.547	0.5272	0.5291	0.5684	0.5873	1.0407
Shanghai	0.7783	1.0196	0.8029	1.0014	1.0351	0.9177	0.8786	0.8136	1.014	1.079
Jiangsu	0.443	0.5087	0.5419	0.5613	0.586	0.6411	0.6966	0.7701	0.845	1.0271
Zhejiang	0.4437	0.493	0.5122	0.5338	0.5481	0.5496	0.6195	0.6448	0.6868	1.0077
Anhui	0.3379	0.3608	0.3588	0.37	0.3851	0.385	0.4049	0.3996	0.4069	0.4473
Fujian	1.0137	1.0016	0.9627	0.6713	0.8216	0.6971	0.8	0.8085	0.8943	1.1226
Jiangxi	0.3293	0.353	0.3496	0.3911	0.4003	0.4082	0.4505	0.4421	0.4773	0.5458
Shandong	0.7088	0.6845	0.5945	0.6342	0.694	0.5003	0.5056	0.5052	0.5327	0.5575
Henan	1.004	0.6278	0.5877	0.5409	0.5564	0.4355	0.4473	0.4272	0.4397	0.489
Hubei	0.5043	0.5737	0.6891	0.7249	1	0.5498	0.6298	0.6249	0.6473	0.7363
Hunan	0.5608	0.5967	0.5552	0.4824	0.4946	0.5006	0.5326	0.4545	0.4571	0.557
Guangdong	1.0106	1.0014	0.6392	0.6643	1.0008	0.6936	1.0047	0.7986	0.8624	1.0797
Guangxi	0.4683	0.7079	0.5264	0.6664	0.6586	0.5511	0.5743	0.5942	0.6319	0.7039
Hainan	0.5127	0.5685	0.5861	0.5995	0.627	0.6397	0.7254	0.7278	0.8058	0.8626
Chongqing	0.3265	0.3758	0.3961	0.4248	0.445	0.4746	0.567	0.5492	0.6236	0.7656
Sichuan	0.4524	0.493	0.5167	0.5185	0.5307	0.5831	0.6528	0.6886	0.7354	0.8916
Guizhou	0.2966	0.3138	0.3602	0.4325	0.5491	0.6919	0.7896	0.9157	1.0302	1.1382
Yunnan	0.2613	0.3005	0.3101	0.3438	0.3505	0.3526	0.3672	0.3981	0.4352	0.5292
Shanxi	0.5111	0.6231	0.6683	0.737	1.0001	0.7612	0.8293	0.8625	0.8948	1.053
Gansu	0.2153	0.2092	0.2161	0.2267	0.2345	0.2301	0.2548	0.2432	0.2621	0.2978
Qinghai	0.496	0.4912	0.5639	0.6149	0.6445	0.6141	0.6691	0.7303	0.8501	1.12
Ningxia	0.3656	0.4078	0.4235	0.4703	0.501	0.5358	0.5558	0.5874	0.6797	0.694
Xinjiang	0.445	0.4174	0.4867	0.5245	0.4206	0.4473	0.4434	0.548	0.7591	1.0263
Average	0.5345	0.5544	0.533	0.5525	0.6024	0.5528	0.5961	0.5925	0.6542	0.7814

The above analysis shows the time series changes and average development trend of agricultural production efficiency. This paper used kernel density estimation to analyze the dynamic evolution process of agricultural production efficiency in China. Figure 1 shows the distribution of kernel density estimates of agricultural productivity from 2010 to 2019.

From Figure 1, the agricultural production efficiency of each region in China changed from a "single-peak" trend to a "double-peak" direction from 2010 to 2019, and the peak value decreased. The bimodal trend shows that the regional agricultural production efficiency tends towards polarization. Agricultural production efficiency in some areas is clustered to a high level, and agricultural production efficiency in some areas is crowded to a low level. However, during the sample period, the peak value decreased significantly. The density distribution curve shifted from a sharp peak to a broad ridge and moved to the right as a whole. It shows that the gap in agricultural productivity has narrowed between regions. They correspond to the results given in Table 1. In addition, the center of the peak density shifted significantly, oscillating between 0.6 and 0.8. The density centers of the minor peaks oscillate between 0.8 and 1.0. The agricultural productivity has generally improved in regions with agricultural productivity between 0.2 and 0.4. The gap in agricultural production efficiency was dramatically reduced, especially in 2016–2019. China is in a period of economic transformation, and economic growth is shifting to high-quality economic development. Agricultural productivity in underdeveloped regions has increased, and the utilization rate of input factors has increased. In addition, agricultural production technologies from developed areas flow to less developed areas, all of which have resulted in a trend of overall growth and narrowing of gaps in the evolution of agricultural production efficiency between regions in China.

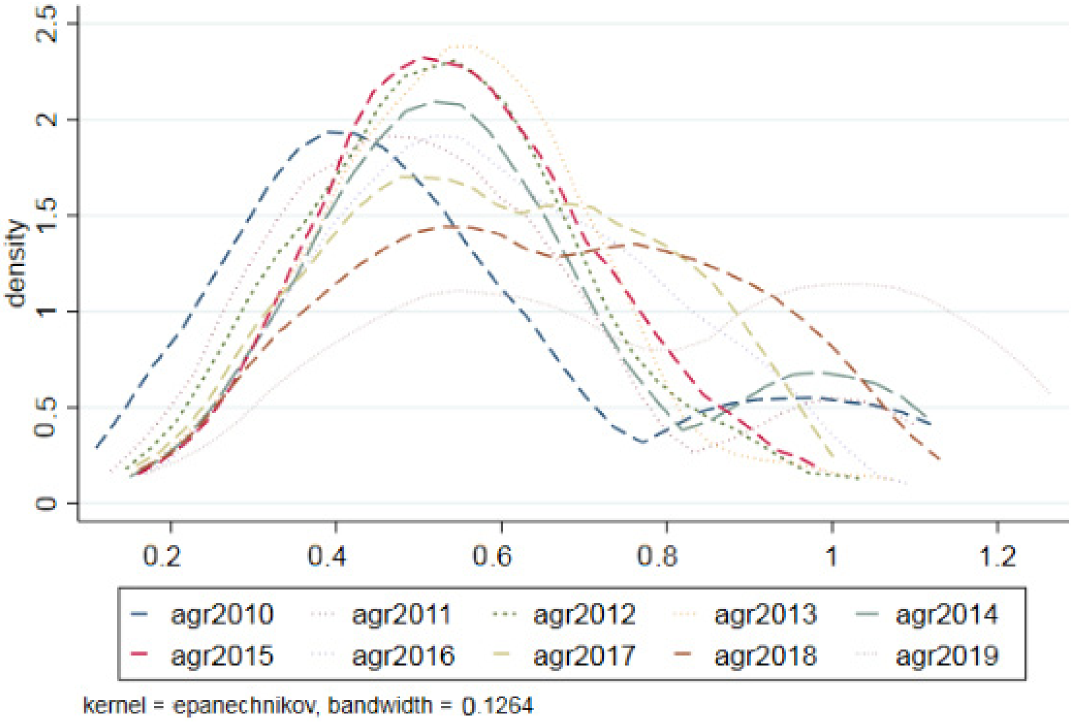

Figure 1. Distribution map of estimated kernel density of agricultural production efficiency in China from 2010 to 2019.

4. Measurement and Result Analysis of Agricultural Carbon Emissions

4.1. Measurement Methods and Data Sources

The explained variable in this paper is agricultural carbon emission intensity. There is no direct statistical caliber for agricultural carbon emissions, and it needs to be estimated based on other indicators. Academia generally believes that carbon emissions in crop planting mainly come from two primary sources. First, production factors such as chemical fertilizers (the raw materials are primarily anthracite coal), pesticides, and plastic films required for agricultural planting also belong to direct carbon emissions. Second, in agricultural production, using electrical energy in rural machinery, such as tillage, irrigation, and transportation, consumes fossil energy, which is indirect carbon emission. Based on this, this paper refers to the estimation method of agricultural carbon emissions by Li Bo (2011) [32], and the estimation of agricultural carbon emissions is shown in Equation (4).

$$car_{j,t} = \sum CO_{2,i} = \sum E_i \cdot \alpha_i \tag{4}$$

where $car_{j,t}$ is the carbon emissions of the j region in the t year. $CO_{2,t}$ is the carbon emission of the i production activity in different areas. The carbon emissions from all production activities are added up to the total carbon emissions of agricultural production in a region. E_i is the amount of carbon emission sources used in production activity i. α_i is the carbon emission coefficient of the i carbon emission source.

Different institutions and scholars have other criteria for determining the carbon emission coefficient of agricultural production. This paper adopts the reference coefficients given by the School of Biology and Technology of China Agricultural University, the IPCC United Nations Intergovernmental Committee of Experts on Climate Change, the Institute of Agricultural Resources and Ecological Environment of Nanjing Agricultural University, and the Oak Ridge National Laboratory of the United States. The details are shown in Table 3.

Table 3. Carbon emission coefficient and sources.

Carbon Emission Source	Carbon Emission Coefficient	Sources
ploughing	312.6 kg C/km^2	School of Biology and Technology of China Agricultural University
Diesel fuel	0.5927 kg C/kg	IPCC United Nations Intergovernmental Committee of Experts on Climate Change
Agricultural film	5.18 kg C/kg	Institute of Agricultural Resources and Ecological Environment of Nanjing Agricultural University
Pesticide	4.934 kg C/kg	Oak Ridge National Laboratory of the United States [33]
Fertilizer	0.8956 kg C/kg	Oak Ridge National Laboratory of the United States
Irrigation	25 kg C/km^2	Dubey and Lal, 2009 [34]

In the calculation of chemical fertilizers as carbon emission sources, the carbon emissions of different types of fertilizers may be quite different, different crops are planted on land, and different amounts of certain chemical fertilizers also cause different CH_4 and N_2O emission factors. According to the research of Hu Xiaokang et al. (2011) [35], in the detection of summer maize soil, the greenhouse effect caused by N_2O-N emission under the conditions of nitrogen fertilizer application of 300 kgN/hm^2, 250 kg N/hm^2, and 185 kgN/hm^2 was 1621.29 kgCO_2/hm^2, 1095.82 kgCO_2/hm^2, and 786.72 kgCO_2/hm^2, respectively. China has a vast territory and abundant resources. The main crops grown in different regions are very different, and the application structures of nitrogen, phosphorus, and potassium fertilizer are also different between regions. Therefore, in the calculation of the carbon emission of chemical fertilizers in this section, the carbon emission coefficient of chemical fertilizers refers to the research data of the Oak Ridge National Laboratory in the United States. This is mainly because, first, the chemical fertilizer carbon emission coefficient given by the Oak Ridge National Laboratory in the United States is widely used in academia and has great reference value; second, according to the research of Chinese scholars on the carbon emission coefficient of NPK fertilizers (Deng M.J. et al., 2016) [36], the average value of the research is consistent with the carbon emission coefficient of fertilizers given by the Oak Ridge National Laboratory in the United States.

The data sources for the estimation of regional carbon emissions in China are the "China Agricultural Statistical Yearbook (Calendar Years)" and the "Statistical Yearbooks (Calendar Years)" of each province, and the "China Rural Statistical Yearbook (Calendar Years)". Considering data availability, excluding the data of Tibet, Hong Kong, Macau, and Taiwan, a total of panel data of 30 provinces in China from 2010 to 2019 were obtained. This paper used this to estimate agricultural carbon emissions.

4.2. Analysis of the Results of Agricultural Carbon Emissions

According to the estimation method of agricultural carbon emissions and the carbon emission coefficients of different carbon sources given above, this paper obtained the carbon emissions of other regions in China from 2020 to 2019. According to the estimated results, the total value of agricultural carbon emissions in China from 2010 to 2019 and the regional Theil index are drawn, as shown in Figure 2.

From Figure 2, the changes in China's agricultural carbon emissions from 2020 to 2019 can be divided into three stages. The first stage was from 2010 to 2013. During this period, the total value of China's agricultural carbon emissions increased steadily. In 2010, 2011, and 2013, the total agricultural carbon emissions of the 30 regions were 291.98 million tons, 294.12 million tons, and 297.74 million tons, respectively. The Theil index of carbon emissions decreased significantly, from 0.2090 in 2010 to 0.2059 in 2013, which indicates that the gap in carbon emissions between regions has reduced. After 2005, the Chinese government implemented a series of policies to increase grain production, and the average carbon emission also increased. The agricultural production in the main grain-producing areas was stable, and the output value of the agricultural output in non-main grain-producing regions increased. In the second stage, from 2013 to 2017, the total value of China's agricultural carbon emissions showed a fluctuating downward trend. In 2014, 2015, and 2017, the total agricultural carbon emissions were 303.33 million tons, 305.17 million tons, and 294.34 million tons, respectively. The Theil index of carbon emissions increased significantly from 0.2059 in 2013 to 0.2155 in 2017. It indicates a widening gap in agricultural carbon emissions in different regions. As China's economy enters a transitional period, agricultural production technologies innovate, and the government emphasizes environmental protection. Crop yields have risen, and average carbon emissions have continued to grow. However, the carbon emissions in a few developed regions decreased instead, which shows that the total amount of agricultural carbon emissions has decreased, while the differences in carbon emissions between regions have expanded. The third stage is from 2017 to 2019, and agricultural carbon emissions dropped significantly. In 2018 and 2019, the total value of agricultural carbon emissions in China's 30 regions was 283.92 million tons and 272.57 million tons, respectively. However, the carbon emission Theil index first rises and then falls, and the time is short, so it is impossible to judge the difference trend of carbon emissions accurately. In terms of general trends, as the government pays more attention to the environment, based on ensuring food security, China's agricultural carbon emissions gradually decreased.

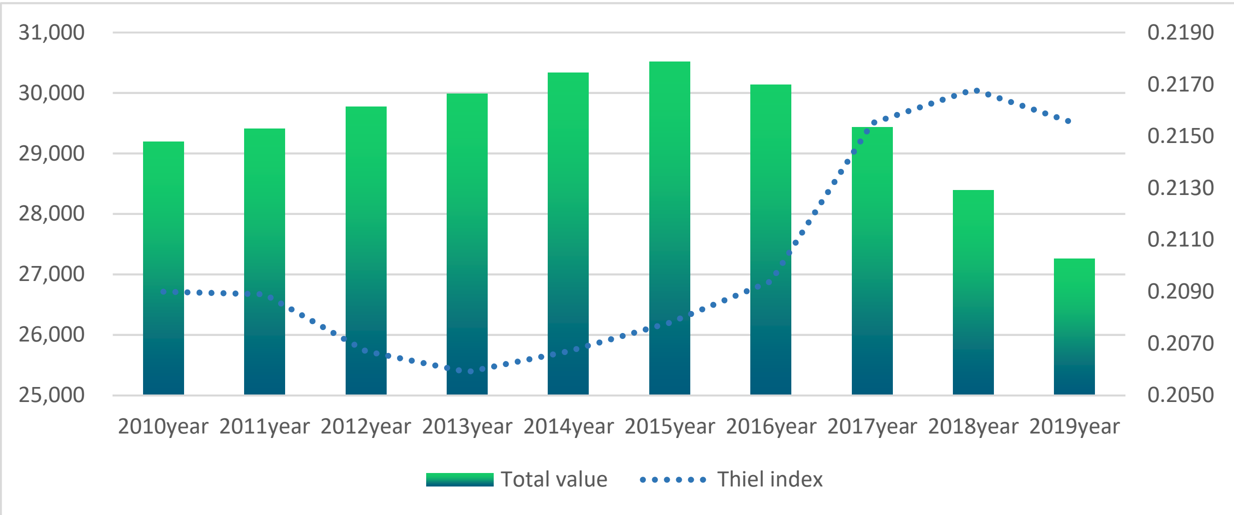

Figure 2. The total value of agricultural carbon emissions in China and the regional Theil index from 2010 to 2019.

In order to investigate the dynamic evolution of agricultural carbon emissions in China, this paper next uses kernel density estimation to analyze it. Due to the slight differences in the kernel density estimates of different farm carbon emissions, Figure 3 only shows the distribution of the kernel density estimates of agricultural carbon emissions in 2010, 2013, 2016, and 2019 in China.

As can be seen from Figure 3, the overall distribution curve of agricultural carbon emission kernel density from 2010 to 2019 first shifted to the right and then moved to the left. It more intuitively reflects the trend of total agricultural carbon emissions increasing first and then decreasing in China, consistent with the results in Figure 2. From the peak changes in the kernel density distribution, the agricultural carbon emissions of each region in China gradually showed an apparent "double peak" trend. The slight difference between the heights of the two peaks indicates that the two ends of the regional agricultural carbon emissions have similar aggregation trends. There is little difference in the number of regions with high levels of carbon emissions and low levels of carbon emissions. In 2019, the direction of the two peaks was obvious. The total amount of agricultural carbon emissions tended to be concentrated and gradually approached the two equilibrium points. As time changes, the area to the left of the peak gradually decreases, while the site to the right gradually increases. It shows that the growth rate of agricultural carbon emissions is relatively fast in low and medium-level regions.

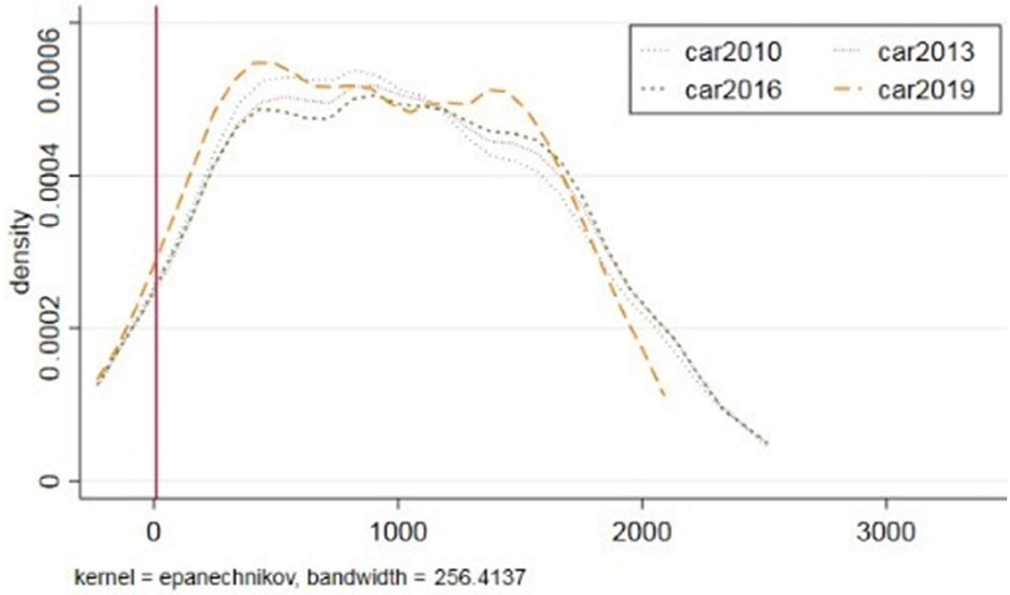

Figure 3. Distribution of Kernel density estimates of agricultural carbon emissions for selected years in China.

In contrast, the increase in agricultural carbon emissions in high-level regions is relatively slow. It corroborates with the Theil index in Figure 2. The difference in agricultural carbon emissions between regions gradually narrows and then continues to expand.

The variation trends and spatial distribution characteristics of carbon emissions in different regions are shown in Figure 4. Figure 4 shows the distribution map of agricultural carbon emissions in China based on agricultural carbon emissions by region in 2010, 2013, 2016, and 2019. The figure divides regional carbon emissions into five groups, namely 50-5 million tons, 501-8 million tons, 801-13 million tons, 1301-18 million tons, and 1801-25 million tons. Then draw a map of the regional distribution of different groups.

From Figure 4, the regional spatial distribution of agricultural carbon emissions varies relatively little in China from 2010 to 2019, with two main characteristics. First, areas with high agricultural carbon emissions are concentrated in the central region of China, dominated by the main grain-producing regions, such as Henan, Shandong, Hunan, and other regions. Areas with low agricultural carbon emissions are concentrated in the coastal regions of China, such as Hainan, Tianjin, Shanghai, Zhejiang, and other regions. It is related to the factor endowment and strategic economic position of China. The central plain region has a suitable climate, four distinct seasons, and abundant land resources, which provide advantages for agricultural development. The eastern coastal region is the window to the world in China's reform and opening up. It plays an important role in the construction of "domestic circulation as the main, domestic and foreign double circulation". It is the key to integrating the world's resources, so there is less arable land and low agricultural carbon emissions in coastal regions. Second, areas with low-level agricultural carbon emissions first decreased and then increased. The number of sites with high levels of agricultural carbon emissions decreased. The regions with agricultural carbon emissions exceeding 18 million tons were Sichuan, Hunan, and Henan in 2010, while seven regions had less than 5 million tons. Based on ensuring the growth of agricultural output value, the growth rate of agricultural carbon emissions is relatively low in most regions. In 2019, two regions with agricultural carbon emissions exceeding 18 million tons, namely Henan and Hunan. There are nine regions with less than 5 million tons, including some central provinces such as Shanxi and Chongqing. The excessive use of agricultural and chemical fertilizers caused a series of negative impacts such as environmental pollution and ecological damage, such as low utilization of chemical fertilizers affecting soil health. In recent years, the No. 1 document of the Central Committee of China has repeatedly emphasized the development of modern agriculture with coordinated resources. To promote the green development of agriculture and reduce agricultural carbon emissions, the first meeting of China's Central Finance and Economics Committee in 2021 proposed to adjust the structure of farming inputs, reduce the use of chemical fertilizers and pesticides, and increase the use of organic fertilizers. It is of great practical significance to limit the input of agricultural production factors such as agricultural fertilizers, improve agricultural production efficiency to mitigate environmental pollution, and reduce agricultural carbon emissions.

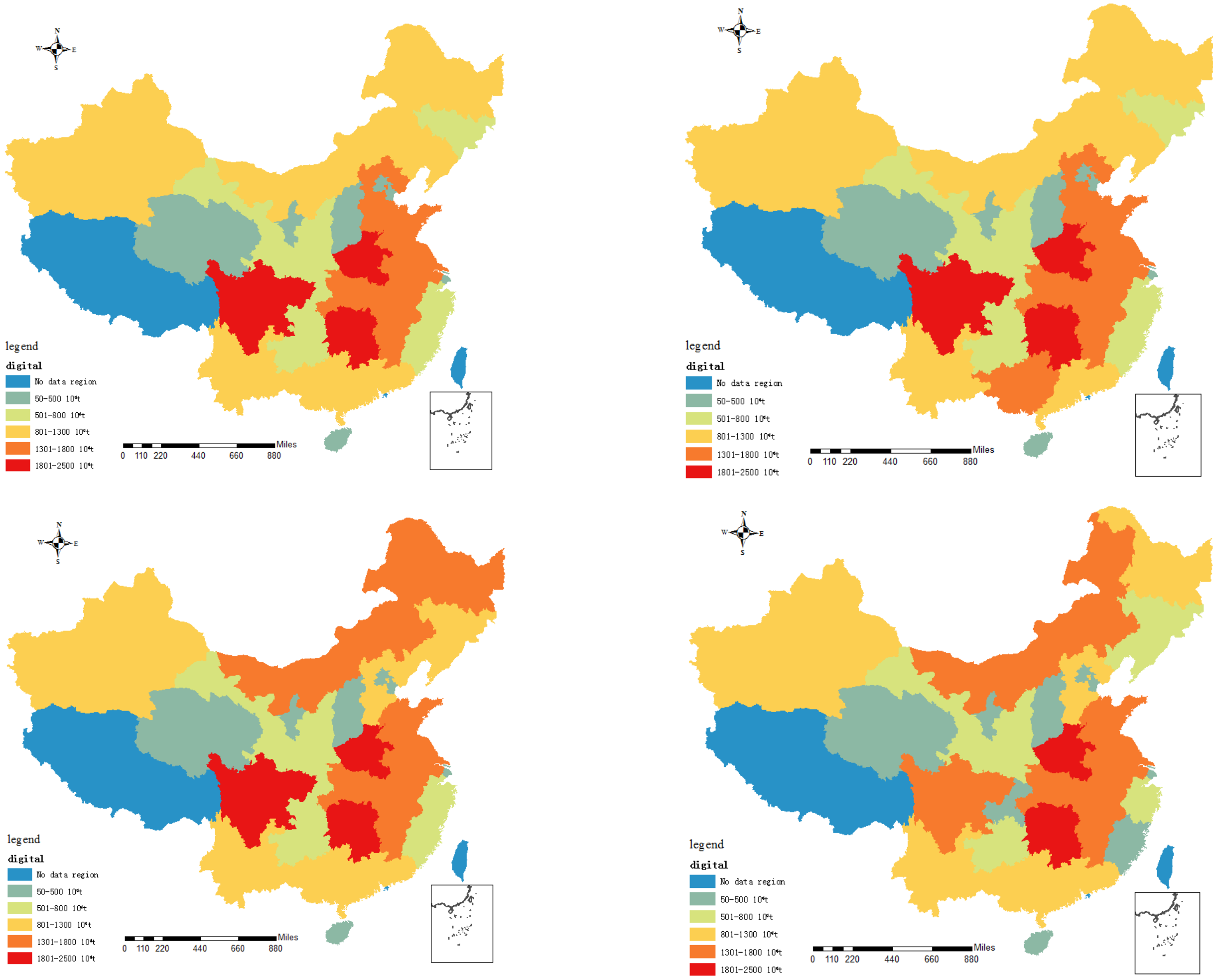

Figure 4. Agricultural carbon emissions by region in 2010, 2013, 2016, and 2019.

5. The Threshold Effect of Agricultural Production Efficiency in China on the Intensity of Agricultural Carbon Emission Intensity

5.1. Threshold Model and Variable Description

Advanced agricultural production technologies can improve efficiency, reducing carbon intensity. However, the improvement of technological level may also lead to an increase in the use of energy in agricultural production and thus increase the carbon intensity of agriculture. The relationship between agricultural production efficiency and agricultural carbon emissions may not be purely linear. Affected by the regional economic development level, urbanization process, geographical factor endowment, industrial structure, etc., there may be heterogeneity between the two. Therefore, this paper uses a nonlinear adjustment mechanism to empirically test the effect of agricultural production efficiency on agricultural carbon emissions. Due to the introduction of cross-terms, the cross form cannot be judged, and it is easily affected by collinearity, and the obtained results are inaccurate. This paper adopts the threshold regression model proposed by Hansen (1999) [37] and uses agricultural production efficiency as the threshold to study the nonlinear relationship between agricultural production efficiency and agricultural carbon emissions. The essence of the threshold model is to use the threshold value to construct a segmentation function and verify the regression effect of the segmentation function. The threshold regression model was established in this paper, as shown in Equation (5).

$$\begin{aligned} CAI_{i,t} = \alpha + \rho_1 Agr_{i,t} \cdot I(Agr < \omega_1) + \rho_2 Agr_{i,t} \cdot I(\omega_1 \leq Age < \omega_2) + \\ \cdots\cdots + \rho_n Agr_{i,t} \cdot I(\omega_{n-1} \leq Agr < \omega_n) + \gamma_n X_{i,t} + u_i + \lambda_t + \varepsilon_{i,t} \end{aligned} \quad (5)$$

variable agricultural carbon emission intensity, $\rho_1, \rho_2 \ldots \rho_n$, is the influence coefficient of agricultural production efficiency (Agr) in different sections. Agr is both a threshold variable and an explanatory variable. $I(\cdot)$ is the indicative threshold function. If the parenthesized expression is true, $I(\cdot) = 1$; otherwise $I(\cdot) = 0$. $\omega_1, \omega_2 \cdots \omega_n$ is the threshold value, which is endogenously determined by the selected sample data.X is the control variable and γ_n is the coefficient of the control variable.u, λ, and ε represent the regional fixed effects, time fixed effects, and random disturbance terms of the regression model, respectively.

This paper lists the explanatory variables, explained variables, and selected control variables based on the threshold regression model.

(1) Explained Variable: Agricultural Carbon Emission Intensity (CAI)

In the previous section, this paper estimated the agricultural carbon emissions of different regions in China from 2010 to 2019. This paper used carbon emission intensity, the carbon dioxide produced per cultivated land unit, and the explained variable. Carbon emission intensity can better reflect the carbon emission level in agricultural production activities compared with carbon emission. Based on this, the carbon emission intensity of agriculture is calculated as shown in Equation (6).

Agricultural carbon emissions intensity:

$$CAI_{i,t} = \frac{car_{i,t}}{(Arable - land)_{i,t}} \quad (6)$$

where $CAI_{i,t}$ refers to the agricultural carbon emission intensity of the i region in the t year, which is also the explained variable in the threshold regression model.$(Arable - land)_{i,t}$ is the cultivated area of the region in the current year. $car_{i,t}$ is the regional agricultural carbon emissions estimated above.

(2) Explanatory variables: agricultural productivity (Agr). The farm production efficiency of 30 regions in China from 2010 to 2019 was measured above.

(3) Control variables: Due to a large amount of literature, this paper selected the following control variables to explain the impact on agricultural carbon emission intensity. The degree of disaster (dis): One of the essential differences between farm production and other industries is that natural conditions significantly affect it. Therefore, this paper chose the degree of agricultural disaster to express and use the ratio of the affected area of crops to the size of arable land to calculate the degree of agricultural disaster. Urbanization level (urb): The civilization process and socialization level of cities also affect rural life and production methods to a certain extent. This paper adopted the proportion of the urban population to the total population at the end of the year to represent the urbanization level. Industry structure (ind): The industrial structure represents the progress of social modernization and the degree of completion of industrialization and profoundly affects the development process of the primary industry. This paper used the ratio of the added value of the tertiary sector to the secondary industry to measure the upgrading of the industrial structure. Resident income level (pci): The living standards of residents in agricultural production areas also affect the intensity of agricultural carbon emissions. In this paper, the average disposable income of urban and rural residents was used to indicate the income level of residents. The quality of the workforce (edu): The labor quality and education level of agricultural producers can affect the awareness of ecological, environmental protection, energy conservation, and emission reduction. Since agricultural production

is not necessarily for all rural residents, and some rural residents were not engaged in agricultural production, this paper used the per capita education years (years) to represent the quality of farm laborers in a region.

The data of the control variables in this paper were obtained from the "China Statistical Yearbook (Calendar)" and the Provincial Statistical Yearbook. Some indicators were calculated based on statistical data. Considering the particularity and data availability of Tibet, Hong Kong, Macao, and Taiwan, the data of these four regions were excluded from data collation. Finally, the panel data of 30 areas from 2010 to 2019 were obtained. Table 4 shows the descriptive statistical analysis of each variable.

Table 4. Descriptive statistical analysis.

Variable	Definition	Mean	Std	Min	Max
AEI	Carbon emission intensity	0.2127	0.1065	0.0875	0.763
Agr	Agricultural productivity	0.5953	0.2179	0.2092	1.138
dis	Degree of disaster	0.1609	0.1189	0	0.6187
urb	Urbanization level	57.72	12.60	33.81	89.6
ind	Industry structure	45.74	9.763	28.6	83.5
pci	Resident income level	2.197	1.1005	0.7	7.22
edu	The quality of workforce	0.0192	0.0050	0.008	0.0345

5.2. Empirical Results

According to the theoretical assumptions in Section 2, there may be a nonlinear relationship between agricultural production efficiency and agricultural carbon emissions. Therefore, this paper used agricultural production efficiency as a threshold variable to verify the effect between agricultural production efficiency and agricultural carbon emissions in China's provinces. The number of thresholds needed to be determined before performing threshold regression. Next, tests were conducted under the null hypothesis of no threshold, presence of a single threshold, the existence of a double threshold, and presence of a triple threshold, respectively. Table 5 presents the *p*-values and critical values derived from the self-sampling method.

Table 5. Regression results of threshold effect test.

			Critical Value		
	F-Value	*p*-Value	1%	5%	10%
Single-threshold test	43.32	0.0567	57.723	44.480	39.943
Double-threshold test	25.87	0.0167	28.864	19.240	15.751
Triple-Threshold Test	4.49	0.7433	24.507	17.137	13.808

Note: *p*-values and critical values are obtained by repeatedly sampling 300 times using the "self-sampling method" (Bootstrap).

From Table 5, the *p*-value corresponding to the triple-threshold test is 0.7433, which fails the 10% significance test, indicating no triple-threshold. The *p*-value for the single threshold was 0.0567, which passed the 10% significance test. The *p*-value for the double-threshold was 0.0167, which gave them a 5% significance test. This shows that the model has both a single-threshold and a double-threshold. In order to more accurately analyze the impact of agricultural production efficiency on agricultural carbon emissions, this paper used a double-threshold model to verify the relationship between the two. Table 5 gives the estimated results and confidence intervals of the threshold value of the double-threshold with agricultural production efficiency as the threshold.

By combining Tables 4 and 5, there was a significant double-threshold effect between agricultural production efficiency and agricultural carbon emissions. From Table 6, the estimated values of the double-threshold variables were 0.8501 and 1.0140, respectively. The 95% confidence interval for the first threshold estimate was [0.8254, 0.8566]. The 95%

confidence interval for the second threshold estimate was [1.0137, 1.0196]. The estimated value of the double-threshold can divide the agricultural production efficiency into three intervals, namely the low agricultural production efficiency region ($Agr < 0.8501$), the medium agricultural production efficiency region ($0.8501 \leq Agr < 1.014$), and the high agricultural production efficiency region ($Agr \geq 1.014$). The regions in the third interval have reached effective agricultural production efficiency from the double-threshold value.

Table 6. Threshold estimation results.

	Estimated Value	95% Confidence Interval
Threshold value ω_1	0.8501	[0.8254, 0.8566]
Threshold value ω_2	1.0140	[1.0137, 1.0196]

Based on the double-threshold estimation results above, this paper estimates the parameters of the double-threshold model. The results of threshold regression are shown in Table 7. The control variables are the same as above, and the related estimation results of the control variables are no longer listed in the table.

Table 7. Threshold regression results.

Variable	Variable Interval	Coefficient (T-Value)
Agricultural production efficiency	$Agr < 0.8501$	0.2749 *** (6.35)
	$0.8501 \leq Agr < 1.014$	−0.8678 * (−1.74)
	$Agr \geq 1.014$	−1.201 ** (2.23)

Note: ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively.

From the results of the threshold regression in Table 7, with agricultural production efficiency as the threshold, the regions in China are divided into low-efficiency regions, medium-efficiency regions, and high-efficiency regions. When the agricultural production efficiency is lower than 0.8501, the agricultural production efficiency promotes the agricultural carbon emission intensity. The coefficient of influence at this point was 0.2749, which passed the significance test at the 1% level. When agricultural production efficiency is in the second interval, the effect of agricultural production efficiency on agricultural carbon emission intensity is negative. The influence coefficient is −0.8678, significant at the 10% level. At this time, the increase in agricultural production efficiency suppresses the intensity of agricultural carbon emissions. When the agricultural production efficiency is more significant than 1.014, that is, when the region reaches the effective agricultural production efficiency, the impact of agricultural production efficiency on agricultural carbon emission intensity is also negative. The influence coefficient was −1.201, and it passed the 5% significance level test.

In contrast, the influence coefficient of agricultural production efficiency in the third interval is more significant than that in the second interval. There are regional differences in the impact of agricultural production efficiency on agricultural carbon emission intensity. The nonlinear relationship between the two presents an "inverted U-shaped" trend. When agricultural production efficiency is low, production efficiency increases the intensity of agriculture carbon emissions. In regions with high agricultural production efficiency, improving agricultural production efficiency instead suppresses carbon emission intensity.

Previous studies focused on the impact of agricultural carbon emissions. The research results of Li B. (2011) [32] showed that labor scale factors, outcome factors, and agricultural production efficiency have a certain inhibitory effect on agricultural carbon emissions. The research results of Wang S. et al. (2020) [38] showed that the agricultural carbon emission intensity in Henan Province presents a spatial distribution pattern of "high in the north and south and low in the middle", and there are large spatial differences in agricultural production efficiency in Henan Province under the constraints of carbon emissions. Different scholars have drawn different conclusions, which also proves that the impact of agricultural production efficiency on agricultural carbon emissions has regional heterogeneity. Yang H.J. et al. (2015) [39] conducted a study using panel data from 31 provinces in China from 2004 to 2012. The conclusion is that China's generalized agricultural production efficiency has a significant threshold effect on agricultural carbon emission reduction, and improving agricultural production efficiency is an effective way to reduce agricultural emissions. This paper draws similar conclusions based on the measurement of agricultural productivity and agricultural carbon emissions in the narrow sense. The nonlinear relationship between China's narrow agricultural production efficiency and agricultural carbon emission intensity presents an "inverted U-shaped" trend.

In regions with low agricultural production efficiency, increased production efficiency increases the intensity of agricultural carbon emission. Two mechanisms of action mainly achieve this process. First, in underdeveloped areas, the improvement of agricultural production efficiency is reflected in the increased efficiency of using agricultural chemical fertilizers and agricultural machinery. The extensive use of chemical fertilizers and the utilization of agricultural machinery in agricultural production activities such as irrigation, tillage, and transportation increased agricultural carbon emissions. Second, the increase in agricultural production efficiency leads to higher yields in farming. An increase in the rate of return leads to more increased investment in agricultural production and an increase in the labor force. The expansion of the farm production scale inevitably leads to higher intensity of agricultural carbon emissions. Once the efficiency of regional agricultural production increases to a certain level, the improvement of agricultural production efficiency suppresses the intensity of agricultural carbon emissions.

On the one hand, after a particular stage of economic development, agricultural economic growth cannot rely solely on expanding the scale of production. It also requires the coordinated development of factors such as optimization of agricultural structure, progress in agricultural science and technology, and modernization of agricultural production methods. The essence of agricultural production efficiency improvement in this process is the factor utilization rate. The utilization rate of input factors such as chemical fertilizers and agriculture has increased, and the input of chemical fertilizers, pesticides, machinery, and other elements per unit area is reduced. However, the output value is still growing. With improved agricultural production efficiency, the intensity of agricultural carbon emissions decreases instead.

On the other hand, resources and technology are heavily invested in agricultural production. The government has imposed restrictions on chemical fertilizers and pesticides on farmland. The development of modern agriculture through scientific and technological progress can reduce environmental pollution and energy consumption. By 2019, a significant portion of the region has not achieved effective agricultural production efficiency. At present, the Chinese government pays more and more attention to the development of low-carbon agriculture to complete the transformation and sustainable development of the agricultural economy. Only after regional agriculture achieves effective production efficiency can the carbon emission intensity of agriculture be reduced based on maintaining food security.

6. Conclusions, Policy Recommendations, and Research Prospects

6.1. Conclusions

This paper established an index system for measuring agricultural production efficiency based on the panel data of 30 regions in China from 2010 to 2019. Then, the super-efficiency SBM model was used to measure the agricultural production efficiency in the different areas. Additionally, its time evolution characteristics were analyzed using kernel density estimation. This paper then proceeded to estimate agricultural carbon emissions using the factor inputs in agricultural production activities and studying the temporal evolution characteristics of agricultural carbon emissions using the Theil index and kernel density estimation. Spatial attributes of regional agricultural carbon emissions were analyzed by depicting their spatial distribution over some years using ArcMap software. Finally, this paper used the threshold regression model to empirically test whether there is a nonlinear relationship between agricultural production efficiency and agricultural carbon emission intensity. The conclusion is as follows:

(1) There are two main characteristics of China's agricultural production efficiency from 2010 to 2019. First, the efficiency of agricultural productivity has steadily increased in most regions. Second, there is a large agricultural production efficiency gap between areas, narrowing gradually with time. China is in a period of economic transformation, and economic growth is shifting to high-quality economic development. Agricultural productivity in underdeveloped regions has increased, and the utilization rate of input factors has increased. Agricultural production technology from developed regions flows to less developed areas. These have resulted in the overall growth and narrowing gap in the evolution of agricultural production efficiency between provinces in China;

(2) China's agricultural carbon emissions changes from 2019 to 2020 can be divided into three stages. In the first stage, the average agricultural carbon emissions increased steadily, while the Theil index of carbon emissions decreased significantly. In the second stage, the gap widened between agricultural carbon emissions in different regions. From 2017 to 2019, the agricultural carbon emissions dropped substantially in the third stage, and it was impossible to judge the trend of difference in carbon emissions accurately. Areas with high agricultural carbon emissions are concentrated in the central region of China. The low-level agricultural carbon emission areas first decreased and then increased; the number of high-level agricultural carbon emission areas decreased. As the government pays more attention to the environment, China's agricultural carbon emissions have gradually reduced to ensure food security;

(3) There are regional differences in the effect of agricultural production efficiency on the intensity of agricultural carbon emissions—the nonlinear relationship between the two shows an "inverted U-shaped" situation. When agricultural production efficiency is low, production efficiency increases the intensity of agriculture carbon emissions. In regions with high agricultural production efficiency, improving agricultural production efficiency instead suppresses carbon emission intensity.

6.2. Policy Recommendations

The above research results show that improving agricultural production efficiency suppresses the intensity of agricultural carbon emissions after the agricultural production efficiency is effective. In addition, in 2020, the Chinese government issued the "Opinions on Doing a Good Job in the Field of "Three Rurals" and Ensuring the Achievement of a Well-off Society in an All-round Way as Scheduled". It clearly put forward policies to strengthen the construction of modern agricultural facilities, strengthen the supporting role of science and technology, promote high-quality development of agriculture, and ensure green development of agriculture. The research of this paper found that the regional narrow agricultural production efficiency can restrain the carbon emission intensity of the planting industry after reaching effective efficiency. The Chinese government also successively introduced policies to limit chemical fertilizers and agricultural applications, which have a greater impact on agricultural producers. For scientific and technological researchers, the current agricultural production technology, and the inability to meet the needs of green production, the backward technology will inevitably be eliminated. Researchers need to strengthen the research and development of agricultural biotechnology and vigorously implement the independent innovation project of the seed industry. At the same time, researchers should also speed up the research and development and application of large and medium-sized, intelligent, and compound agricultural machinery and support the mechanization of farmland in hilly and mountainous areas. For farmers in the plantation industry, government restrictions on the agricultural application of chemical fertilizers may affect yields to some extent. Farmers need to improve their knowledge of agricultural production, rationally apply chemical fertilizers, reduce the impact of national policies on production activities, and increase output. For agricultural and sideline product processing enterprises, they should cooperate with national policies. More detailed and strict standards are needed for purchasing agricultural products, and green production efficiency needs to be improved in the production process.

To achieve a win–win situation between food security and environmental benefits, we must first improve the efficiency of green agricultural production and increase crop yields. At the same time, it is also necessary to formulate environmental regulations for agricultural production based on considering regional heterogeneity to give full play to the low-carbon orientation function of the government. Therefore, this paper puts forward specific policy recommendations as follows:

First, improve agricultural technology and promote the development of agricultural modernization. Agricultural technological progress is not only an inevitable requirement of agricultural modernization but also a significant initiative to implement the rural revitalization strategy. As China's industrialization enters the middle and late stages, industry feeds back on agriculture. The government has increased investment in agricultural development and formulated a series of supportive policies to subsidize agricultural production, but supporting agriculture alone can only regulate the institutions of agricultural production. It is also necessary to strengthen agricultural technological innovation and actively promote the creation of agricultural production machinery, chemical fertilizers, and other production materials. At the same time, reduce agricultural carbon emissions and take the road of clean and efficient green agricultural development.

Second, develop agriculture according to local conditions. Agriculture is the foundation of the national economy. Agricultural production in the narrow sense is more constrained by regional factor endowments. Therefore, it is necessary to formulate policies according to local conditions to address the regional gap in the impact of agricultural production efficiency and agricultural carbon emission intensity. We give play to regional advantages and develop the agricultural economy based on ensuring national food security. The developed eastern regions lack the geographical endowment to establish agriculture on a large scale. Therefore, it is possible to vigorously introduce advanced technologies and management concepts from foreign developed agricultural fields based on high agricultural production efficiency. At the same time, rationally allocate farming resources and the environment and generate radiation effects to drive the green development of agriculture in the surrounding areas. Agriculture should be developed vigorously in the central and western regions, especially Henan, Hunan, and other provinces. Develop particular agricultural industries based on guaranteed production, and increase the export volume of high-quality agricultural products. Increase the efficiency of the agricultural output from the perspective of improving output value, and promote the transformation of agricultural resource utilization to a green production model with low emissions, low input, and high output.

Third, limit pesticides and chemical fertilizers, and establish an agricultural green economy assessment system. Excessive use of agricultural and chemical fertilizers pollutes the environment, increases agricultural carbon emissions, and damages soil health. Therefore, local governments should formulate restrictions on the input of pesticides, chemical fertilizers, and other factors according to the characteristics of local agricultural development. On the one hand, reducing the redundancy of farming resources, promoting the rational use of agricultural factor resources, and protecting the ecological environment in rural areas. On the other hand, it increases the construction of rural educational facilities. Cultivate the awareness of agricultural producers to protect the environment and low-carbon production. At the same time, the government also promotes end-of-line treatment technology and low-carbon clean production and upgrades traditional agriculture. In addition, a set of agricultural green economic accounting systems needs to be formulated, including agricultural carbon emissions and agricultural economy. Regional governments incorporate environmental protection and low-carbon agricultural development into regional economic growth to achieve a harmonious farm economy and ecological environment development.

6.3. Research Prospects

China has become a significant carbon emitter, and the growth of agricultural carbon emissions cannot be underestimated. After the reform and opening-up, China's agricultural economy has developed at the cost of high emissions and environmental damage to a certain extent. The Chinese government has gradually begun to pay attention to environmental protection and agricultural carbon emission reduction. It is essential to take agricultural production efficiency as the research object and study the agricultural carbon emission reduction path. There are still some shortcomings in this paper. Limited by the data availability, the characteristics of agricultural development in rural areas have not been studied separately. The following research can explore agricultural carbon emissions from rural revitalization. The scope of the sample data can also be extended to the data of prefecture-level cities, taking the urban agglomeration as the research object. We can further improve the research on agricultural carbon emissions, provide a viable path for transforming China's agricultural production model to a low-energy, high-efficiency green production model, and then promote the high-quality development of Chinese agriculture.

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