agriculture

Article

The Significance of Agricultural Modernization Development for Agricultural Carbon Emission Efficiency in China

Suhan Zhang [1,2,†], Xue Li [1,2,3,†], Zhen Nie [1,2], Yan Wang [1,2], Danni Li [1,2], Xingpeng Chen [1,2,4], Yiping Liu [5] and Jiaxing Pang [1,2,4,*]

1 College of Earth and Environmental Sciences, Lanzhou University, Lanzhou 730000, China; 220220949120@lzu.edu.cn (S.Z.); lx20@lzu.edu.cn (X.L.); niezh2023@lzu.edu.cn (Z.N.); 220220949111@lzu.edu.cn (Y.W.); 220220949060@lzu.edu.cn (D.L.); chenxp@lzu.edu.cn (X.C.)
2 Key Laboratory of Western China's Environmental Systems (Ministry of Education), Lanzhou University, Lanzhou 730000, China
3 Guangdong Guodi Plannig Science Technology Co., Ltd., Guangzhou 510630, China
4 Institute of Ecological Civilization Construction Research and Assessment, Lanzhou University, Lanzhou 730000, China
5 School of Economics, Lanzhou University, Lanzhou 730000, China; liuyiping@lzu.edu.cn
* Correspondence: pangjx@lzu.edu.cn
† These authors contributed equally to this work.

Abstract: Agricultural production contributes to the increase in global carbon emissions. It is crucial to improve output and reduce carbon emissions in the context of agricultural modernization, for which improved carbon emission efficiency is key. However, the role of agricultural modernization in promoting agricultural carbon emission efficiency is not clear. Hence, the aim of this article is to analyze the spatiotemporal evolution of agricultural modernization and agricultural carbon emission efficiency in China from 2000 to 2019 and to reveal the relationship between agricultural modernization and agricultural carbon emission efficiency. The results showed that (1) in China, the overall level of agricultural modernization has been steadily increasing, and the regional differences are widening, showing a spatial pattern characterized by a gradual decline from the eastern and central regions to the western region. (2) China's agricultural carbon emission efficiency continues to grow but has not achieved a data envelopment analysis (DEA) effect, with the eastern and western regions having higher agricultural carbon efficiency than the central region. The regional differences first narrow and then expand. (3) Agricultural modernization significantly promotes agricultural carbon emission efficiency in both the province and the neighboring provinces, and the interprovincial spillover effect exceeds the direct effect within the province. A nonlinear correlation exists between agricultural modernization and agricultural carbon emission efficiency.

Keywords: agricultural modernization; agricultural carbon emission efficiency; spatial spillover effect; spatial threshold effect

Citation: Zhang, S.; Li, X.; Nie, Z.; Wang, Y.; Li, D.; Chen, X.; Liu, Y.; Pang, J. The Significance of Agricultural Modernization Development for Agricultural Carbon Emission Efficiency in China. *Agriculture* **2024**, *14*, 939. https://doi.org/10.3390/agriculture14060939

Received: 16 May 2024
Revised: 12 June 2024
Accepted: 13 June 2024
Published: 16 June 2024

1. Introduction

Agriculture provides the material basis for human survival, as well as employment and income for agricultural workers. It guarantees food security as well as social stability and development. Despite facing challenges posed by urbanization and arable land degradation, China's agriculture feeds 21% of the world's population on 7% of the world's arable land [1] and maintains an agricultural GDP growth rate of 4.6% per year [2]. Meanwhile, China has a high production of vegetables and fruits and is now the world's largest exporter of vegetables [3]. Although China has a high self-sufficiency rate in food, it is predicted that [4] the increased imports over the next 10 years will account for 3–5% of total consumption, with little impact on the sustainability of Chinese agriculture. However, it is worth mentioning that Chinese agriculture is also facing challenges due to climate change, urbanization, and aging, and thus agricultural modernization (AM) plays a crucial role in the sustained increase in agricultural production. However, the pursuit of agricultural output is accompanied by challenges to agricultural sustainability. Traditional Chinese agriculture is constrained by smallholder economic production methods and is therefore highly dependent on resource consumption and infrastructure inputs [5]. Thus, Chinese agriculture generates some environmental problems, and agricultural carbon emissions, in particular, contribute to climate change. As a major carbon emitter, China's agricultural carbon emissions account for 16–17% of GHG [6], which is higher than the U.S. (6–7%) [7] and the global average (10–12%). Although there are differences in land use between China and the U.S., agricultural output and productivity in the U.S. have reached a high level, so the modernization of agricultural production in the U.S. can provide a certain reference experience for China's agricultural production. Despite China's commitment to aim for a 2030 carbon emission peak and carbon neutrality by 2060 [2], considering that agricultural development in the past has long been in a "high-carbon" mode, indicating high inputs, consumption, and pollution, there are numerous obstacles to reducing this extent of carbon emissions in a short period of time [8]. Therefore, China needs to enhance AM, increase its expected agricultural output, reduce carbon emissions, and enhance the agricultural carbon emission efficiency (ACEE), thus building a low-carbon agriculture and achieving China's "dual-carbon" goal.

AM is the process of using advanced science and technology, managerial techniques, and ideology to elevate traditional, backward agriculture to a sophisticated level [9]. AM should take green development as its premise, upgrade the production and management system as its foundation, and improve quality and efficiency as its key attributes; moreover, technical support is required to guarantee AM. Currently, China is implementing the strategy of rural revitalization, which provides the impetus for the further implementation of AM. In fact, agricultural production generates large volumes of carbon emissions [10], so it is important to use the techniques of AM to increase agricultural output, reduce carbon emissions, and improve the ACEE. Scholars usually consider the ACEE as the level of agricultural productivity under the constraint of carbon emissions [11], indicating that the higher its value, the more rational the allocation of resources, while the goal of AM is to increase the utilization of agricultural resources, and the two have a close intrinsic relationship. Recently, there has been abundant research on AM as well as the ACEE and the factors influencing them, but the main focus has been on evaluating the level of both individually, with fewer studies on the relationship between the two.

Developing AM and reducing carbon emissions by improving the ACEE are two important directions in future agricultural development, and in order to achieve a "win–win" outcome, the relationship between the two needs to be clarified [12]. Meanwhile, it is worth noting that the research on how AM affects the ACEE is currently insufficient. In addition, most of the previou studies measure ACEE using the slack-based measure (SBM)—Undesirable model, with the disadvantage that the optimal decision-making units (DMUs) cannot be compared [13]. Therefore, the aims of this paper are as follows: (1) Building on past studies, we analyze the temporal and spatial distribution characteristics of AM and ACEE in China by constructing scientific indicators and applying the super-efficient SBM-Undesiable model. (2) Investigating the impact of AM on ACEE, reveal the spatial spillover effect and nonlinear relationship between the two, and put forward policy suggestions to realize the sustainable development of Chinese agriculture. This paper briefly reviews the previous literature on AM and ACEE in Section 2, lists the data and methodology in Section 3, provides the results in Section 4, discuss the current problem and future works in Section 5, and summarizes the conclusion and policy implications in Section 6.

2. Literature Review

AM is an important topic in academic research; however, currently, China's AM is still at the primary stage of development [10], while foreign research began in the mid-20th century [14,15]. Rich results have been obtained from the quantitative examination and analysis of the AM level. In terms of research objectives, AM emphasizes green development and sustainability [16–18], technical support [19,20], business models [21], etc. In terms of the selection and construction of indicators, the indicators of AM in developed countries focus on four dimensions: economic, environmental, pollution, and development [22,23]. Lobão et al. [24] constructed the Agricultural Modernization Index (AMI) to analyze AM in the Brazilian Amazon. Kansanga et al. [25] found that the machinery level can accelerate AM. Based on the definition and connotation of AM, domestic scholars have established detailed measurement systems. Yang et al. [10] divided AM into ecological modernization, management modernization, and production modernization. Xia et al. [26] constructed five first-level indices covering management practices. Yet, the choice of the AM index varies from province to province due to the different development conditions and current situation. In terms of measurement, the TOPSIS method [27,28], the entropy method [23,27], the DEA method [29], and the multi-index measurement method are often used, among which the multi-index measurement is the most objective and therefore the most widely used [29].

Carbon emission efficiency (CEE) is an indicator that combines economic inputs and outputs with carbon emissions, as undesired outputs affect economic inputs associated with land, capital, and labor; therefore, CEE is applied in different sectors [8]. For the conceptualization of CEE, Kaya defined CEE as GDP output per unit of CO_2 [30], while Mielnik [31] defined it as CO_2 per unit of energy consumption. With regard to methodology, the ACEE is usually measured by Malmquist [32] and DEA [33]. Currently, scholars' studies on the ACEE include the evaluation indexes [34], influences [35], and the decoupling effect from economic growth [36].

ACEE research is closely linked to the definition of carbon emission sources. Johnson [37] suggested that agriculture carbon emissions mainly originate from agricultural fossil fuel use, animal enteric fermentation and manure management, paddy fields and croplands, deforestation and agricultural burning, and fertilizer use. Tian et al. [38] selected 23 major carbon emission sources from agricultural production species, with enteric fermentation, manure management, paddy fields, and agricultural material inputs accounting for a high proportion of carbon emissions. Fertilizers, pesticides, animal manure, biomass fuel, and changes in soil structure [39] are the major global sources of agricultural carbon emissions. Regarding the factors influencing ACEE, some scholars [11] have found that labor size suppresses agricultural carbon emissions, and agricultural industry structure and urbanization promote ACEE. Ye [40] found that agricultural industrial agglomeration has an inverted U-shaped nonlinear effect on agricultural environmental efficiency. Furthermore, Xie [41] analyzed technical efficiency by using the urban–rural integration index and found that it has a detrimental effect on frontier technological progress, and is hence inimical to the promotion of ACEE and that regional economic development is a significant factor constraining urban–rural integration and ACEE. Agriculture is highly dependent on regional resource endowments, but similarities in regional production conditions make ACEE spatially relevant. Wu et al. [42] measured the ACEE of crop production through GB-US-SBM, showing a decreasing and then increasing trend, and also suggested that agricultural materials account for the highest share of carbon emissions in China. Additionally, they concluded that the ACEE of the eastern and western regions showed σ-convergence, whereas the whole country showed conditional β-convergence. This indicated that the development of neighboring regions affected the regional ACEE.

In summary, the ACEE is limited by the labor force size, regional production conditions, technology, urbanization, and the structure of the agricultural industry, while in the process of AM, more advanced production technologies and national policies indirectly affect these factors [26,43], which in turn have an impact on the ACEE [44]. Therefore, there is an inevitable relationship between AM and agricultural production. Nevertheless, the literature on relationships between AM and ACEE is very limited. Considering the above background, while promoting AM and achieving carbon peaking and neutrality targets are priorities for future development in China, current studies on AM and ACEE focus on evaluating the two separately, and relatively few systematic studies have explored the interrelationships between AM and ACEE. Therefore, to guarantee agricultural sustainability, it is imperative to investigate the correlation between AM and ACEE in the agricultural sector.

3. Materials and Methods

Since data for Tibet, Taiwan, Hong Kong, and Macau were not available, we studied 30 provincial units in China. Based on the current situation, the national development policies, and the classification criteria of previous scholars [45], we divided the studied regions into eastern, central, and western regions.

Data for the evaluation index system of AM levels come from the officially released yearbook and EPS database. Due to a lack of data, we estimated the agricultural carbon emissions in 30 Chinese provinces, which were calculated using Equation (3).

3.1. Calculation of AM

The Communist Party of China's 19th National Congress put forward the goal of AM construction; based on the connotation of AM, we built an evaluation index system of AM level using 4 first-class index components: production and management system, quality benefits, green development, and support and protection. As shown in Table 1, the weight of indexes is identified using the entropy method. The formula is as follows:

$$AM = \sum_{j=1}^{m} w_j \, p_{ij} \tag{1}$$

where m is the number of indicators, and w_j is the weight of the j-th indicator; $p_{ij} = \frac{Y_{ij}}{\sum_{i=1}^{n} Y_{ij}}$, and $Y_{ij} = X_{ij} + 1$, X_{ij} is obtained by normalizing the positive and negative values.

The agricultural production and management system is a symbol of the degree of organization, socialization, and marketization; the level of modern agricultural productivity; and guaranteed food security and the red line of arable land. The indicators for measuring the agricultural production and management system include 6 second-class indexes, namely stability in rice and wheat production; the proportion of livestock production value in the total agricultural output value; the proportion of the added value of agriculture, animal husbandry, forestry, and fishing industry services to the added value of agriculture, animal husbandry, forestry, and fishing industry sectors; the added value of primary production as % of GDP; agricultural mechanization; and the effective irrigation rate. In terms of the quality benefits produced by AM, a total of 4 second-class indexes were selected. Agricultural labor productivity and the agricultural land output rate were selected to measure production efficiency and rural residents' disposable income per capita, and the rural Internet penetration rate reflected the effectiveness of AM. The old development model of high yield and high pollution can no longer be adapted to the new era, and AM involves the realization of sustainability. Accordingly, evaluating AM needs to cover green development as first-class index; therefore, water and energy consumption attributed to CNY 10,000 of the added value of agriculture, forestry, animal husbandry, and fishing industry, and the extent of pesticide and fertilizer reduction were selected as measures. Due to the weakness and uncertainty of the agricultural sector, the development and diffusion of agricultural technologies require government support. The proportion of expenditure on agriculture, forestry, and water conservancy of the added value of agriculture, forestry, animal husbandry, and fishing; agricultural loan inputs for fishing, forestry, animal husbandry, and agriculture per unit; and the depth of agricultural insurance were used as second-class indexes to measure the extent of local government support for agricultural development.

Table 1. Evaluation index system of AM level.

First-Class Index	Second-Class Index	Description	Attribution	Weights (%)
Agricultural production and management system	Stability in rice and wheat production (%)	Rice and wheat production in the current year/Average production over the last five years	+	2.20
	Proportion of livestock production value in total agricultural output value (%)	(Animal husbandry output value + fishing industry output value)/Total output value of agriculture, animal husbandry, forestry and fishing industry	+	8.43
	The proportion of added value of agriculture, animal husbandry, forestry, and fishing industry services to the added value of agriculture, animal husbandry, forestry, and fishing industry sectors (%)	Added value of agriculture, animal husbandry, forestry, and fishing industry services/Added value of agriculture, animal husbandry, forestry, and fishing industry	+	4.64
	Added value of primary production as % of GDP (%)	Added value of primary sector/GDP	+	8.30
	Agricultural mechanization (kw/hm^2)	Total power of agricultural machinery/cultivated land area	+	11.56
	Effective irrigation rate (%)	Effective irrigated area/cultivated land area	+	6.20
Quality benefits	Agricultural labor productivity (10,000 CNY/person)	Added value of agriculture, animal husbandry, forestry, and fishing industry/number of primary industry workers	+	8.83
	Agricultural land output rate(10,000 CNY/hm^2)	Added value of agriculture, animal husbandry, forestry, and fishing/sown area	+	5.62
	Rural residents' disposable income per capita (CNY 10,000)	Obtained directly	+	9.11
	Rural Internet penetration rate (%)	Rural telephone subscribers at year-end/Total rural households	+	7.56
Green development	Water consumption of CNY 10,000 of the added value of agriculture, forestry, animal husbandry, and fishing industry (m^3)	Agricultural water use/Value added in agriculture, forestry, animal husbandry, fishing	−	2.05
	Energy consumption of CNY 10,000 of the added value of agriculture, forestry, animal husbandry, and fishing industry (ton of standard coal)	Total energy consumption/Value added in agriculture, forestry, animal husbandry, and fishing industry	−	1.94
	Proportion of pesticide reduction (%)	(Current year's pesticide use—previous year's pesticide use)/previous year's pesticide use	−	1.86
	Proportion of fertilizer reduction (%)	(Current year's fertilizers use—previous year's fertilizers use)/previous year's pesticide use	−	1.47

Table 1. *Cont.*

First-Class Index	Second-Class Index	Description	Attribution	Weights (%)
Support and protection	The proportion of expenditure on agriculture, forestry, and water conservancy of the added value of agriculture, forestry, animal husbandry, and fishing (%)	Spending on agriculture, forestry, and water conservancy/Added value of agriculture, forestry, animal husbandry, and fishing	+	3.97
	Agricultural loan inputs for fishing, forestry, animal husbandry, and agriculture per unit (%)	Balance of agriculture-related loans/Added value of agriculture, forestry, animal husbandry, and fishing industry	+	10.48
	Depth of insurance in agriculture (%)	Agricultural premium income/Added value of agriculture, forestry, animal husbandry, and fishing industry	+	5.78

Note: + indicates the direction of action is positive; − indicates the direction of action is negative.

3.2. Calculation of ACEE

The traditional DEA method is a nonparametric boundary analysis method based on a radial perspective that does not take into account slack variables, cannot deal with non-desired outputs, and does not give a true reflection of the value of ACEE. Tone put forth a nonradial approach (SBM) to improve the reliability of efficiency evaluations, which measures slack variables as well. However, to solve errors due to slack variables [46], which result from the existence of "undesired outputs", and to meet the need to effectively separate several DMUs, they then proposed the super-efficiency SBM—Undesirable model. The super-efficient SBM—Undesirable model was adopted to measure ACEE in this research. The specific formula is as follows [47]:

$$X_j = \left\{x_{1j}, x_{2j}, \ldots, x_{ij}, \ldots, x_{mj}\right\} \in R_{m\times n},$$

$$Y_j = \left\{y_{1j}, y_{2j}, \ldots, y_{ij}, \ldots, y_{q_1 j}\right\} \in R_{q_1\times n},$$

$$B_j = \left\{b_{1j}, b_{2j}, \ldots, b_{ij}, \ldots, b_{q_2 j}\right\} \in R_{q_2\times n},$$

$$ACEE = min\frac{1+\frac{\frac{1}{m}\sum_{i=1}^{m} s_i^-}{x_{ik}}}{1-\frac{1}{q_1+q_2}\left(\frac{\sum_{r=1}^{q_1} s_r^+}{y_{rk}}+\frac{\sum_{t=1}^{q_2} s_t^{b-}}{b_{tk}}\right)} \tag{2}$$

$$s.t.\begin{cases} \sum_{j=1,j\neq k}^{n} \lambda_j x_j + s^- \le x_k \;,\; i=1,\cdots,m \\ 1 \\ \sum_{j=1,j\neq k}^{n} \lambda_j y_j - s^+ \le y_k \;,\; r=1,\cdots,q_1 \\ 1 \\ \sum_{j=1,j\neq k}^{n} \lambda_j b_j + s^{b-} \le b_k \;,\; t=1,\cdots,q_2 \\ 1 \\ 1-\frac{1}{q_1+q_2}\left(\frac{\sum_{r=1}^{q_1} s_r^+}{y_{rk}}+\frac{\sum_{t=1}^{q_2} s_t^{b-}}{b_{tk}}\right) > 0 \\ 1 \\ \lambda_j, s_i^-, s_r^+, s_t^{b-} \ge 0 \,,\, j=1,\cdots n \,,\, j\neq k \end{cases}$$

where s_i^-, s_r^+, ands_t^{b-} are slack variables for input factors, desired output, and undesired output factors, respectively; x_{ik}, y_{rk}, andb_{tk} are the i-th input factor of the k-th DMU, the r-th desired output, and the t-th undesired output element. i = 1, 2, 3, . . ., m; r = 1, 2, 3, . . . , q_1; t = 1, 2, 3, . . ., q_2; j = 1, 2, 3, . . ., n; λ are the constraint conditions.

Agricultural carbon emission was considered an undesirable output variable, according to the literature [38,48,49]. Carbon emissions in this paper were considered mainly those generated by agricultural production, including three main categories: CH_4 and N_2O emissions from enteric fermentation and fecal management during ruminant farming; CH_4 from rice growth; and CO_2 from agricultural land use, including carbon emissions resulting from activities such as agricultural fertilizers, pesticides, mulch films, diesel use in agricultural machinery, land plowing, and irrigation. They did not include natural soil CO_2 emissions. The formula is as follows:

$$C = \sum Ci = \sum Ti \times \delta_i \tag{3}$$

where C denotes the total agricultural carbon emissions in tonnes, C_i denotes total carbon emissions from various carbon sources (livestock and poultry farming, rice cultivation, and land use), T_i denotes the i-th source's activity level, and δ_i denotes the i-th source's emission coefficients. The carbon emission coefficients for different carbon sources have been studied [50–52].

Drawing on existing research, we selected 8 input indicators, the added value of agricultural output, and the desired and undesired outputs of carbon emissions for ACEE measurement [53,54]. The selected input–output indicators were all direct data to maintain the uniformity of statistical caliber. Since measuring ACEE in eastern, central, and western regions individually is not in line with the principle of DEA model measurement [55], the national data of 30 provinces were uniformly selected for measurement. Specific input–output indexes and index descriptions are provided in Table 2.

Table 2. Evaluation index system of ACEE.

Index	Variables	Description
Resource input	Land input	Crop sown area/1000 hm^2
	Pesticides inputs	Pesticides use/10,000 t
	Labor input	Employment in the primary sector/10,000 people
	Mechanical input	Gross power of agricultural machinery/10,000 kw
	Water input	Effective irrigated area/1000 hm^2
	Fertilizer input	Agricultural fertilizer applications/10,000 t
	Agricultural film input	Agricultural film use/10,000 t
	Energy input	Agricultural diesel use/10,000 t
Expected output	Agricultural output	Added value of agriculture, forestry, animal husbandry, and fishing industry/CNY 100 million
Undesirable output	Carbon emission	Agricultural carbon emission/10,000 t

3.3. Spatial Correlation

The core idea of spatial correlation stems from Waldo Tobler: A correlation exists between all things, and the correlation grows stronger with proximity [56]. The global spatial correlation presents the overall spatial distribution property [57,58]. The subsystems' spatial distribution property is determined using the local spatial correlation test, which is usually tested using Moran's I scatter plot and LISA agglomeration plot.

3.3.1. Global Spatial Correlation

$$Moran's\ I = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij}\left(Y_i - \overline{Y}\right)\left(Y_j - \overline{Y}\right)}{S^2 \sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij}} \tag{4}$$

where $S^2 = \frac{1}{n}\sum_{i=1}^{n}(Y_i - \overline{Y})\overline{Y} = \frac{1}{n}\sum_{i=1}^{n} Y_i$, n values represent the 30 provinces, Y_i and Y_j denote ACEE in provinces, and W_{ij} is a geospatial weight matrix that describes the neighboring relationship between regions.

3.3.2. Local Spatial Correlation

Anselin [58] proposed a local Moran's I, or LISA index, which measures the extent to which neighboring regions are spatially correlated with the region. There is a localized situation of high–high aggregation and low–low aggregation when local Moran's I > 0. Otherwise, it indicates the high–low aggregation and low–high aggregation. It is expressed as follows:

$$Moran's\ I_i = \frac{(Y_i - \overline{Y})\sum_{j=1}^{n} W_{ij}(Y_j - \overline{Y})}{S^2} \tag{5}$$

3.3.3. Setting of the Spatial Weighting Matrix

Since agricultural carbon emissions are influenced by similar climatic and geographic environments, as well as by the economic policies of neighboring economic units, a spatial weight function is needed to characterize the interrelated effects. Based on geographic adjacency and spatial distance proximity, we set 0–1 adjacency weight matrix and geographic distance weight matrix.

According to spatial adjacency, an adjacency can have both a common boundary and a common vertex. The 0–1 adjacency weight matrix is a Queen-based first-order adjacency matrix with the following expression:

$$w_{01} = \begin{cases} 1,\ i\ and\ j\ are\ adjacent \\ 0,\ i\ and\ j\ are\ not\ adjacent \end{cases} \tag{6}$$

The spatial weight matrix was constructed using Geoda software 1.22 platform, and Hainan was set to be neighboring Guangdong due to its special geographical location in southern China.

Geographic distance weight matrix: The inverse of the distance can reflect the attenuation of spatial unit associations in relation to geographic distance, based on which the power of the distance can be increased depending on whether the role of distance is to be emphasized or not; the higher the weight, the greater the role of the closer point. To emphasize distance, the inverse of the distance squared is used, and the distance between the geographic centers of the two regions is denoted by d, with the following expression:

$$w_{ij} = \begin{cases} \frac{1}{{d_{ij}}^2},\ i \neq j \\ 0,\ i = j \end{cases} \tag{7}$$

3.4. Kernel Density Estimation

Kernel density estimation is a nonparametric method used to study the characteristics of random variables such as the number of distributions, the orientation of distributions, and the distribution of agglomerations in a certain region; it is a tool for studying the uneven spatial distribution and dynamic evolution laws [59]. The function is expressed as follows:

$$f(x) = \frac{1}{Nh}\sum_{i=1}^{N} K\left(\frac{X_i - x}{h}\right) K(x) = \frac{1}{\sqrt{2\Pi}} exp\left(-\frac{x^2}{2}\right) \tag{8}$$

where $K(\cdot)$ represents the kernel function, N is the number of observations, X is the number of observations, and x is the mean average of the observations; h is the bandwidth, the choice of which affects the estimation results as it determines the smoothness of the kernel density curve and the estimation accuracy. The curve is smoother, and the estimation accuracy decreases with increasing bandwidth.

3.5. Empirical Model

The agricultural carbon emission has spatial autocorrelation, as indicated by Moran's I. Therefore, the Spatial Durbin Model was constructed to examine their influencing factors. As SDM incorporates SAR and SEM, which include the dependent and independent variables' spatial correlation, it can well reflect the externality and spatial spillover effects triggered by different influencing factors. To ensure that SDM cannot be simplified to SAR and SEM models, before estimating the model, the Wald and LR tests were run. The results of the parameter analysis reject the null hypothesis and support SDM as the optimal model. The basic expression of the SDM is as follows:

$$y_{it} = \rho \sum_{j=1}^{n} w_{ij} y_{it} + \beta\, x_{it} + \delta \sum_{j=1}^{n} w_{ij} x_{it} + \mu_i + \gamma_t + \varepsilon_{it} \tag{9}$$

where y represents the explained variable, ρ is the spatial regression coefficient; δ is the independent variable's spatial lag coefficient; w_{ij} is the geo-spatial matrix; x is the explanatory variable; β, μ, and γ are the parameters to be estimated, the individual effect, and the time effect, respectively; and ε is the disturbance term. If $\delta = 0$ and $\rho \neq 0$, the SDM model can be simply reduced to SAR; otherwise, SDM can be simply reduced to SEM.

In this study, ACEE was selected as an explained variable, which was calculated by the super-efficient SBM—Undesirable model. AM in each province was selected as the core explanatory variable, which was calculated through the entropy method.

3.6. Panel Threshold Model (PTM)

ACEE varies throughout provinces, such as Hainan, Guangdong, Beijing, and other provinces where ACEE has reached the level of super-efficiency, while Gansu, Jilin, and other provinces are still in the initial stage. Therefore, we chose the panel threshold model proposed by Hansen [60] to identify the threshold effect of AM on ACEE. The specific formula is as follows:

$$\begin{aligned} ace_{it} &= \alpha + X_{it}\delta + \beta_1 am_{it} I(am_{it} \leq \gamma_1) + \beta_2 am_{it} I(\gamma_1 \leq am_{it} \leq \gamma_2) + \cdots \\ &+ \beta_n am_{it} I(am_{it} > \gamma_n) + \varepsilon_{it} \end{aligned} \tag{10}$$

where ace_{it} is the explained variable; am_{it} is the core explanatory variable, which is the threshold value; X_{it} denotes the control variable; and ε_{it} is the random error term.

We selected the level of economic development, urbanization rate, industrialization, technological innovation, the openness of agricultural products, and the disaster's scope as control variables. The level of economic development (gdp) is represented by GDP; the urbanization rate (urb) is represented by the ratio of the urban population to the total population; industrialization (indus) is represented by the ratio of the value added of the industry to GDP; technological innovation (rdjf) is represented by the ratio of the internal R&D expenditure to GDP; the openness of agricultural products (open) is represented by the total amount of import and export of the agricultural products; and the disaster's scope (dis) is represented by the area of the affected area of the agriculture.

4. Results

4.1. General Characteristics of AM

4.1.1. Overall Trend of AM

To directly determine the changes in China's AM, we applied the kernel density to examine the unevenness of AM and the overall kernel density map was obtained, as shown in Figure 1.

In terms of distribution position, the curve as a whole shifts to the right, but the shift is small, indicating that AM, on the whole, exhibits a slow growth trend. In terms of time distribution, the height of the curve decreases significantly, and the width expands significantly from 2000 to 2019, indicating that the overall gap in AM has continued to widen with the passage of time. In terms of curve distribution, the curve shows different degrees of "double peaks" or even "triple peaks", indicating that China's AM has a multipeak pattern, which shows the phenomenon of multi-polarization and demonstrates that regional variations exist in AM growth. Additionally, the right tail of the kernel density curve lengthens each year. The distribution has a tendency to spread to a certain extent, implying that the spatial gap in AM is gradually widening nationwide.

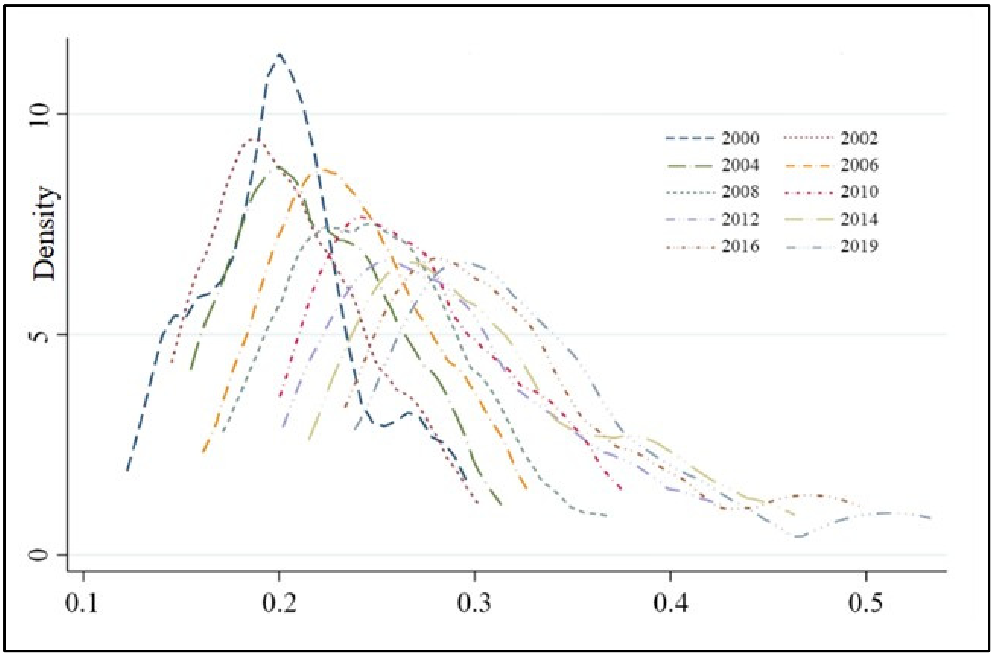

Figure 1. Kernel density map of AM in China.

4.1.2. Spatiotemporal Evolution Characteristics of AM

Figure 2 shows that the level of AM increased, but the pace of development was slow. The level of AM increased from 0.201 in 2000 to 0.349 in 2019, with a slow upward trend and an average annual increase of 2.94%, which could be roughly divided into two phases. In the first phase (2000–2015), AM grew at a faster rate, with an average annual growth rate of 3.21%. However, in the second phase (2015–2019), the growth rate of AM slowed down with an average yearly growth rate of 1.95%. Regionally, AM in the three major regions grew steadily, showing a gradually decreasing spatial pattern from eastern to central and western regions. Throughout the study period, AM in the eastern region was greater than the national average level, followed by the central and western regions, both of which were lower than the national level. The central region had an AM of 0.18 in 2000 and 0.32 in 2019, while the western region had 0.17 in 2000 and 0.30 in 2019. In contrast, the eastern region's agricultural development was more rapid, as evidenced by the fact that the region had an AM of 0.24 in 2000 and 0.42 in 2019, with a higher average yearly growth rate of 2.99% compared to the central (2.89%) and western regions (2.91%). Similarly, only the eastern region had an average yearly growth rate that exceeded the national average, further indicating that AM in the eastern region was developing well. With the advantage of reform and opening up, the eastern region has faster economic development, better infrastructure conditions, more investment in agriculture and industry, more opportunities to attract investment in the countryside, and a more advanced level of agricultural technology, all of which drive the development of AM.

To further reveal the spatial changes in China's AM, using ArcGIS 10.8 to visualize the AM, the data from 2000, 2005, 2010, 2015, and 2019 were selected. The natural break method is based on the distribution pattern of the data and avoids the interference of human factors, so we selected this method to analyze the spatial distribution and defined it according to the five levels divided into low, medium–low, medium, medium–high, and high levels. Figure 3 presents the results.

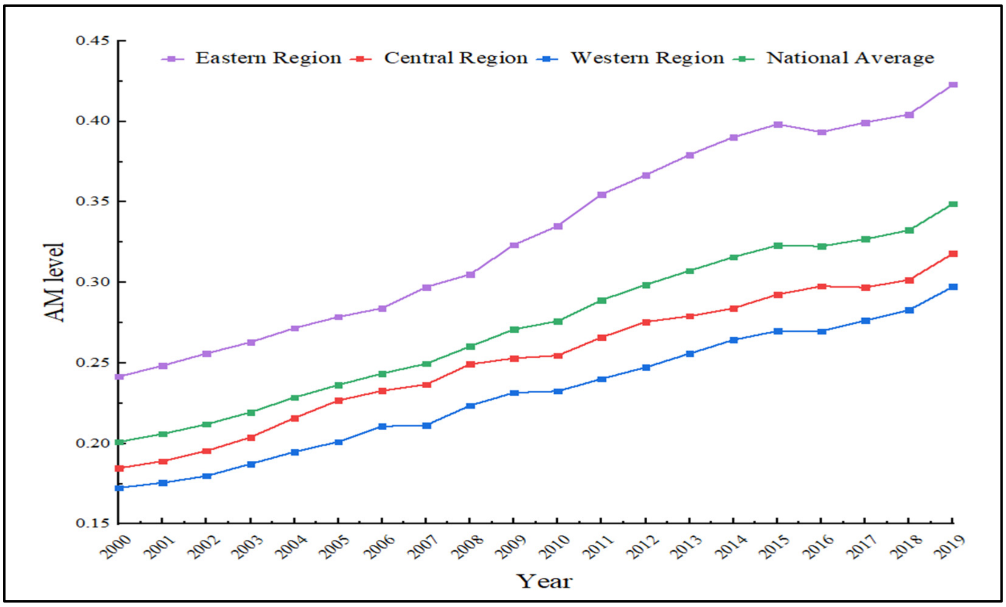

Figure 2. Variation in China's AM over time.

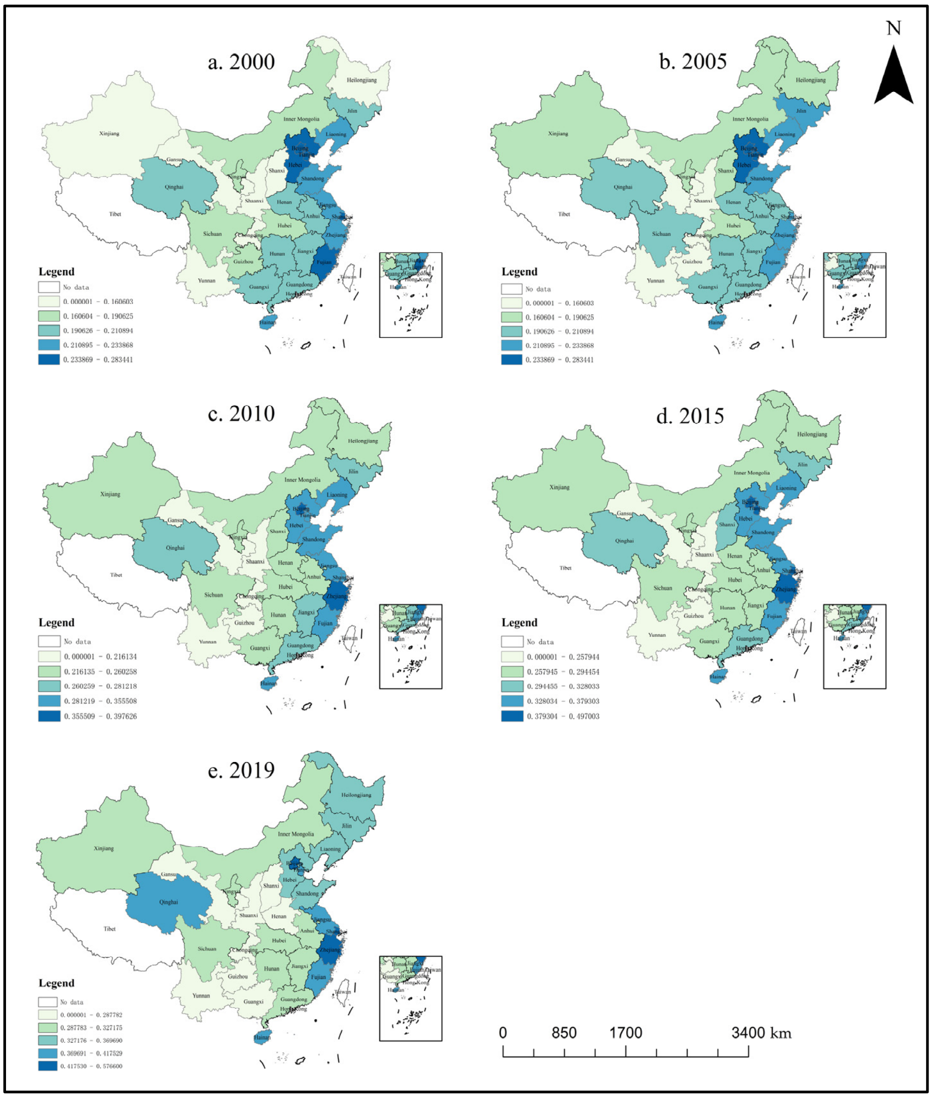

Figure 3. Spatiotemporal of AM in China.

The overall AM across the studied region is in an upward trend, with a spatial cluster distribution and significant regional differentiation, exhibiting a gradual decline from the eastern coastal region to the central and western regions. Specifically, high and medium–high levels of AM dominate in the eastern coastal region, medium and medium–low levels of AM dominate in the central region, and low levels of AM mainly occur in the western region. In terms of spatial and temporal evolution, the differences between regions have become progressively greater. AM in 2000 and 2005 was predominantly at a medium level, which accounted for 26.67% and 30%, respectively, and occurred throughout the central and western regions, at which point it was relatively balanced across regions. In 2010 and 2015, AM was predominantly at a medium–low level, accounting for 36.67% of the total, and all low-value areas were in the central and western regions. In 2019, AM occurred at low and medium–low levels, accounting for 56.67%, and low-value areas were also all located in central and western regions. From 2000 to 2019, a large area centered on Beijing and Zhejiang was basically formed; specifically, in the eastern region, AM has occurred at a high level in Beijing, whereas AM efforts in Fujian, Zhejiang, Shanghai, and Jiangsu have been at medium–high or high levels. Moreover, AM in the central region shifted from a predominantly medium level to a predominantly medium–low level. Although AM in the western region has been increasing, Gansu, Shaanxi, Chongqing, and Yunnan have undergone growth at a slower pace than other provinces, resulting in their low levels of AM. This might be because Gansu, Chongqing, Yunnan, and Shaanxi have complex topography and landscapes, with plateaus and mountains spread across their territories, and the natural conditions of the land are poor, making it difficult to carry out large-scale agricultural production, thus having a constraining effect on AM.

4.1.3. Spatial Agglomeration Characteristics of AM

Table 3 shows the Global Moran's I of AM level from 2000 to 2019. At the 1% significance level, AM passed the z-test, and every coefficient was positive, which indicates that the regions with high levels of AM were spatially neighboring each other, and the regions with low levels of AM were also spatially neighboring each other. Under the geographical weight matrix of AM, Moran's I index fluctuation decreased, indicating a decrease in the degree of spatial agglomeration, which may be because the choices of the development path of AM in different regions became diversified by economic growth.

Table 3. Global Moran's I of AM.

Year	0–1 Neighborhood Weight Matrix	Year	0–1 Neighborhood Weight Matrix	Year	Geographic Distance Weighting Matrix	Year	Geographic Distance Weighting Matrix
2000	0.517 ***	2010	0.619 ***	2000	0.110 ***	2010	0.163 ***
2001	0.592 ***	2011	0.603 ***	2001	0.124 ***	2011	0.167 ***
2002	0.612 ***	2012	0.612 ***	2002	0.130 ***	2012	0.165 ***
2003	0.568 ***	2013	0.598 ***	2003	0.115 ***	2013	0.171 ***
2004	0.548 ***	2014	0.586 ***	2004	0.123 ***	2014	0.166 ***
2005	0.567 ***	2015	0.584 ***	2005	0.137 ***	2015	0.168 ***
2006	0.515 ***	2016	0.542 ***	2006	0.114 ***	2016	0.152 ***
2007	0.509 ***	2017	0.521 ***	2007	0.125 ***	2017	0.140 ***
2008	0.550 ***	2018	0.469 ***	2008	0.143 ***	2018	0.113 ***
2009	0.595 ***	2019	0.439 ***	2009	0.155 ***	2019	0.099 ***

Note: *** represents the significance at the 1% level.

To further analyze the types of spatial agglomeration and spatial anomalies of AM in local areas, we used data from 2000, 2005, 2010, 2015, and 2019 to analyze local spatial correlation patterns, with LISA clustering maps, as shown in Figure 4.

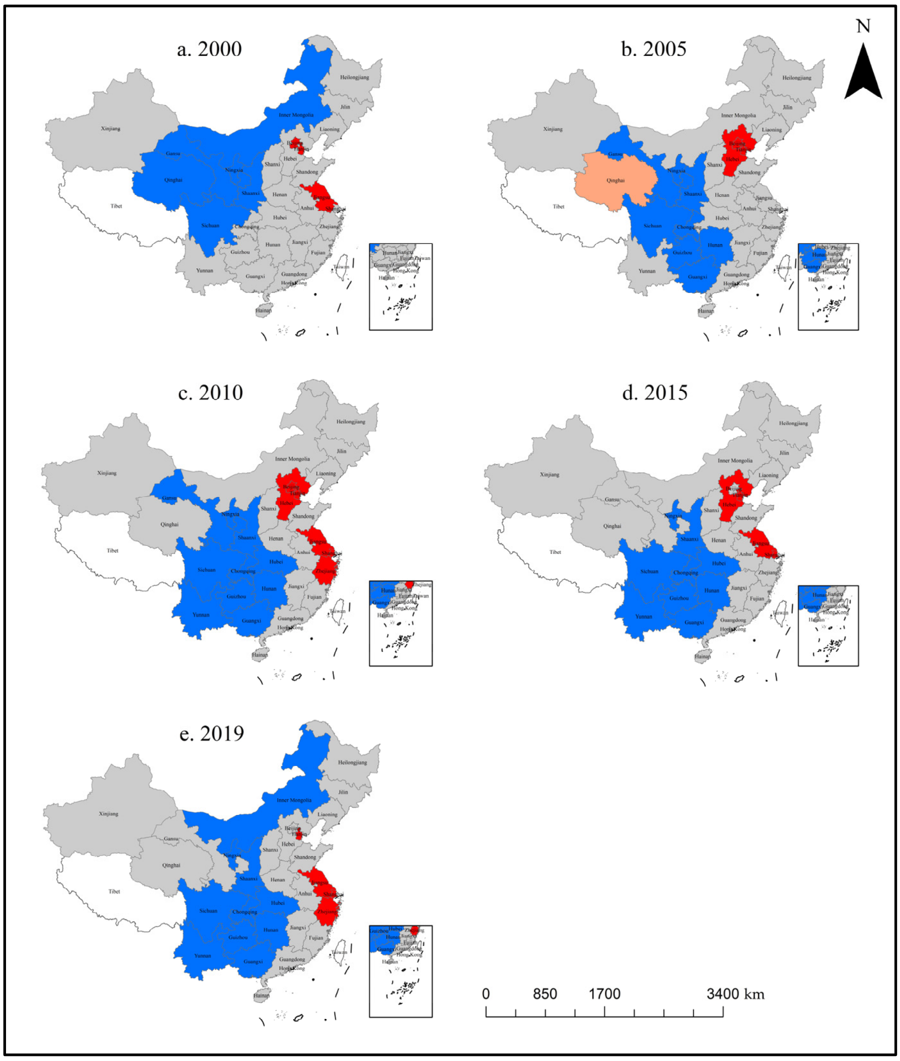

Figure 4. LISA cluster maps of AM in China.

The LISA maps of AM indicate that H-H are clustered in the eastern region, while L-L are clustered in central and western regions. Meanwhile, China's AM resulted in a high-level agglomeration area with Tianjin as the center and a low-level agglomeration area on Sichuan, Shaanxi, and Ningxia. Considering these five stages, the Beijing–Tianjin–Hebei region and Yangtze River Delta are often developed at an H-H, while Shaanxi, Ningxia, Hunan, Guangxi, Chongqing, Yunnan, and Guizhou are frequently developed at an L-L. In China, AM has a varied spatial distribution, with significant spatial spillover effects.

4.2. General Characteristics of ACEE

4.2.1. Overall Trend of ACEE

Based on the calculated results of ACEE in the 30 Chinese provinces, 10 time points were selected at one-year intervals starting from 2000 for kernel density estimation to analyze the distribution of ACEE (Figure 5). In 2000, the ACEE of all provinces was about 0.2 (except Hainan), and Hainan reached the super-efficiency level in 2000, resulting in the right-trailing anomaly of the kernel density curve in 2000. In terms of the distribution position, the density curve of ACEE has a tendency to shift to the right, showing that the ACEE in 30 provinces is increasing. Regarding the changes in the curve shape, its height first rises and then falls, and the width of the main peak first narrows and then expands, indicating that the interprovincial differences in the ACEE first decrease and then increase. The curve changes from a single peak to a double peak, and the distance between the two peaks becomes larger, which means that there is a clear polarization of the ACEE across provinces.

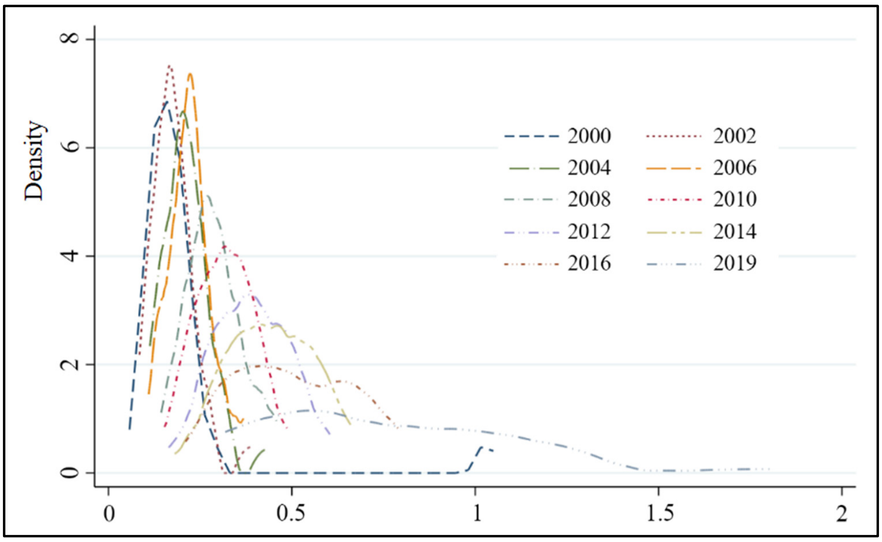

Figure 5. Kernel density map of ACEE in China.

4.2.2. Spatiotemporal Evolution Characteristics of ACEE

China's overall ACEE showed continuous and rapid growth, with an ACEE of 0.19 in 2000 and 0.75 in 2019 and an average annual growth rate of 27.20% (Figure 6); however, the overall ACEE was below 0.8 during the study period and never reached an effective threshold in DEA, indicating that although low-carbon agriculture in China is improving rapidly, there is still immense potential for improving the quality of the agricultural economy. From a regional perspective, the three main regions' ACEE steadily increased, but there were differences in regional development levels, showing a spatial pattern of eastern regions > western regions > central regions. In the process of sustainable agricultural development, the eastern area applies stricter design and implementation guidelines and is at a higher level in terms of the corresponding technical elements and management, while the western region has richer land resources and diversified types of natural environment, with a vast area of arable land and fragile ecological conditions of its own, with building an eco-civilized society being more prioritized. The central region, except Shanxi, is the primary grain-producing region with a large area of cultivated land; however, the realization of comprehensive agricultural production capacity in the main grain-producing area requires higher input of production materials, resulting in lower ACEE [61].

Based on the data from 2000, 2005, 2010, 2015, and 2019, the ACEE of each province was ranked using the natural break method and categorized into low, medium–low, medium, medium–high, and high levels according to the grading results.

According to Figure 7, from 2000 to 2019, China's ACEE continued to grow and showed significant spatial differentiation, manifested as relatively high ACEE in the eastern coastal region and western region and relatively low ACEE in the central region, with an overall spatial evolution pattern of diffusion from the eastern coastal and western regions to the central region. Meanwhile, ACEE in the southern region of China was significantly higher than that in the northern region. Specifically, the high-value areas of ACEE were mainly distributed in Hainan, Guangdong, and Fujian in the eastern region, as well as Sichuan, Qinghai, and Xinjiang in the western region, forming high-value agglomerations centered on the southeastern and northwestern regions. The low-value areas of ACEE were mainly distributed in Heilongjiang and Shanxi in the central region and Gansu in the western region, with a cluster of low values centered in the central and northern parts of China. Among all the provinces, ACEE in Hainan Province was at a high level in all four time periods, while ACEE in Gansu Province was always at a low level. Thus, its ACEE needs to be further improved.

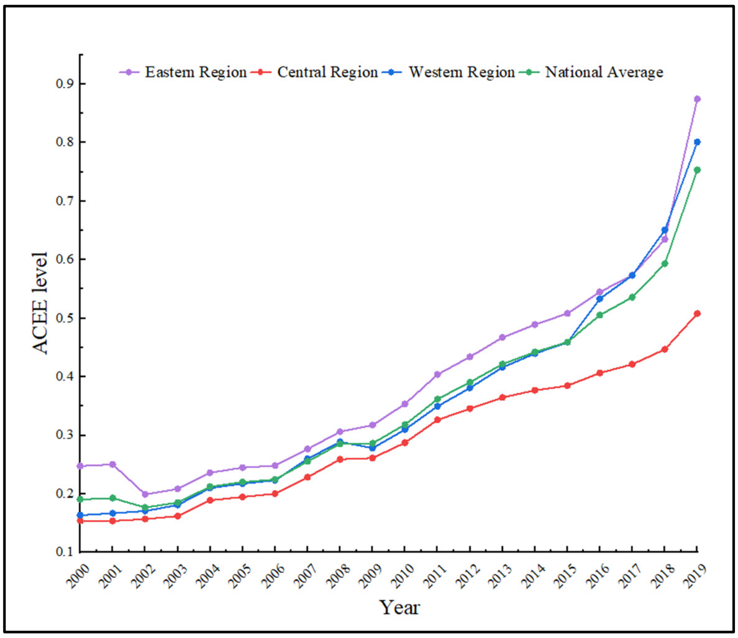

Figure 6. Variation in China's ACEE over time.

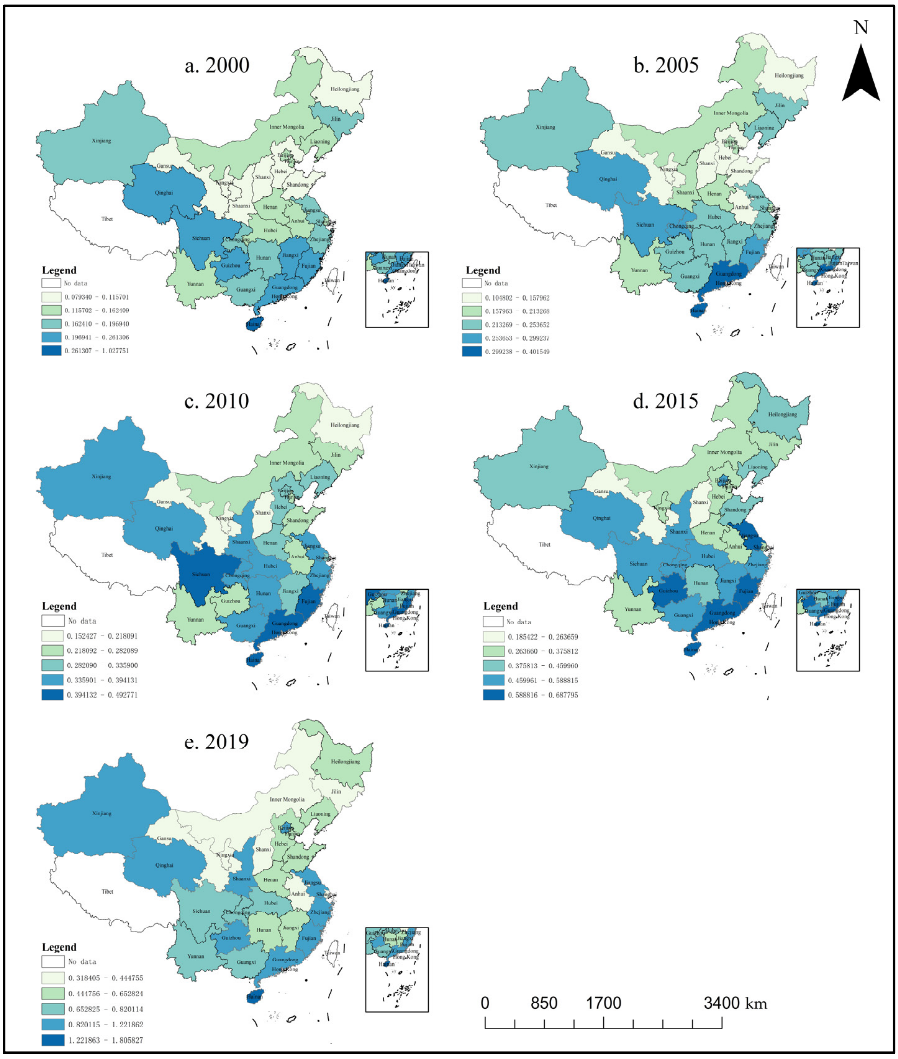

Figure 7. Spatiotemporal distribution of ACEE in China.

4.2.3. Spatial Agglomeration Characteristics of ACEE

Table 4 shows that the global Moran's I of China's ACEE coefficients are all positive and significant, suggesting that areas with high ACEE are adjacent to each other, and areas with low ACEE are also spatially adjacent to each other. Moran's I of ACEE shows fluctuations, with a gradual increase from 2000 to 2006, indicating that the spatial agglomeration of ACEE increased, with a fluctuating decrease after reaching the peak in 2006. This is due to the implementation of targeted low-carbon agricultural policies in various regions, resulting in a more independent ACEE, which weakened the spatial agglomeration. The global Moran's I was 0.211 in 2019, compared with 0.153 in 2000, indicating a more positive spatial correlation of China's ACEE.

Table 4. Global Moran's I of ACEE.

Year	0–1 Neighborhood Weight Matrix	Year	0–1 Neighborhood Weight Matrix	Year	Geographic Distance Weighting Matrix	Year	Geographic Distance Weighting Matrix
2000	0.153 ***	2010	0.310 ***	2000	0.019 ***	2010	0.054 ***
2001	0.138 ***	2011	0.289 ***	2001	0.013 ***	2011	0.066 ***
2002	0.410 ***	2012	0.253 ***	2002	0.065 ***	2012	0.046 **
2003	0.434 ***	2013	0.217 **	2003	0.071 ***	2013	0.020 *
2004	0.376 ***	2014	0.226 ***	2004	0.061 ***	2014	0.025 *
2005	0.432 ***	2015	0.272 ***	2005	0.071 ***	2015	0.057 ***
2006	0.462 ***	2016	0.257 ***	2006	0.086 ***	2016	0.073 ***
2007	0.360 ***	2017	0.245 **	2007	0.048 **	2017	0.072 ***
2008	0.286 ***	2018	0.249 **	2008	0.030 **	2018	0.062 ***
2009	0.359 ***	2019	0.211 **	2009	0.060 ***	2019	0.025 **

Note: ***, **, and * mean significant at the levels of 1%, 5%, and 10%, respectively.

To further analyze the types of spatial agglomeration and spatial anomalies of ACEE in local areas, data from 2000, 2005, 2010, 2015, and 2019 were selected to analyze local spatial correlation patterns, with LISA clustering maps. The results are shown in Figure 8. From the LISA maps of the ACEE, it was found that H-H aggregation areas were clustered in the southern region centered on Guangdong, while L-L aggregation areas in the northern region centered on Hebei and Inner Mongolia.

4.3. Spatial Econometric Analysis of the Impact of AM on the ACEE

To verify whether there was significant collinearity between the variables that affected the estimation of the model parameters, we used the VIF (variance inflation factor) test (Table 5). The result of the VIF test showed that all VIF values were less than 10, which indicated that there was no significant multi-collinearity between the variables.

Table 5. VIF test for variables.

Variables	VIF	1/VIF
am	3.09	0.324
gdp	2.62	0.381
urb	3.15	0.318
indus	1.26	0.797
rdjf	2.54	0.394
open	2.84	0.353
dis	1.22	0.816
Mean VIF	2.39	

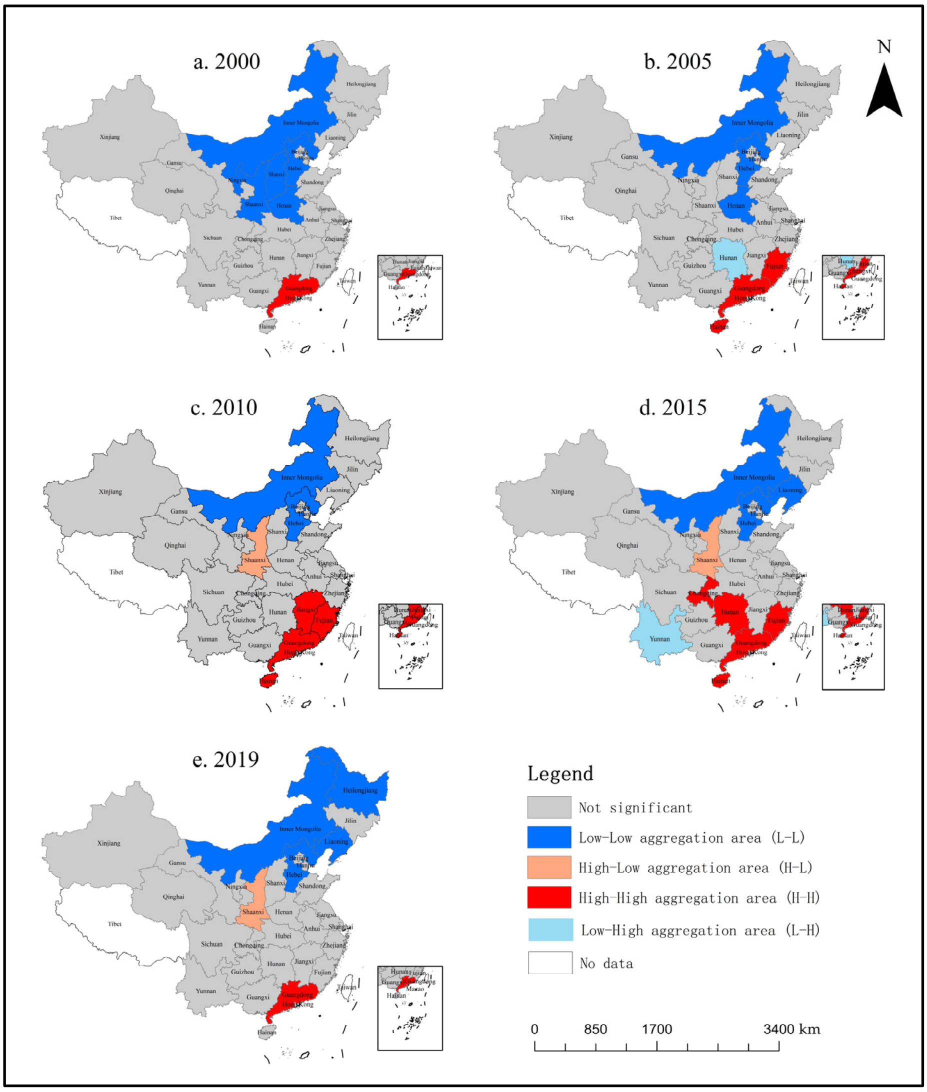

Figure 8. LISA cluster maps of ACEE in China.

Since both AM and ACEE are spatially autocorrelated (Tables 3 and 4), selecting an appropriate spatial econometric model is crucial for the estimation process.

First, we applied the LM (robust) test to select which spatial econometric model to use. Table 6 shows the LM and robust LM test results, which indicate that the SDM model is suitable for studying the spatial effect of AM on ACEE. Meanwhile, the Wald test and the LR test were used to determine whether SDM could be converted into SAR and SEM. Further, SDM did not degenerate into SAR and SEM models as the spatial lag and spatial error coefficients were significant at the 1% level, at which time the SDM was the optimal fit model. Additionally, the Wald test was used for testing, and the *p*-value was determined, which led us to reject the null hypothesis, reaffirming SDM's superiority over the other models. In addition, the Hausman test (H0: presence of random effects) statistics were negative at −4.59 and −19.73, respectively, so the fixed-effect model performed better than the random-effect model; these results were also combined with the R^2 results to select the SDM with individual fixed effects. Therefore, we employed the SDM with a fixed-effect model to test the spatial spillover effect of AM on ACEE.

Table 6. Identification test of the spatial econometric model.

Test	0–1 Neighborhood Weight Matrix	Geographic Distance Weighting matrix
LM (lag) test	171.180 ***	234.706 ***
Robust LM (lag) test	92.053 ***	116.239 ***
LM (error) test	84.115 ***	132.421 ***
Robust LM (error) test	4.989 **	13.954 ***
LR test (SDM or SAR)	26.53 ***	34.06 ***
LR test (SDM or SEM)	71.49 ***	87.55 ***
Wald test	63.77 ***	55.45 ***

Note: *** and ** mean significant at the levels of 1% and 5%.

4.3.1. Estimation Results of SDM

According to Table 7, the examination of the spatial spillover effect of ACEE showed that the spatial autoregressive coefficients of the two matrices were 0.378 and 0.425, respectively, both passing the 1% significance test. This shows that there is a significant spatial interaction effect of the ACEE between the neighboring provinces. Regions with a higher ACEE undergo spatial agglomeration and can promote the ACEE in neighboring provinces through the diffusion of advanced technologies and successful agricultural production experiences.

Table 7. Estimation of SDM model with two weight matrices.

Variables	0–1 Neighborhood Weight Matrix	Geographic Distance Weighting Matrix
am	0.397 * (0.205)	0.506 *** (0.191)
gdp	0.000 *** (0.000)	0.000 *** (0.000)
urb	−0.001 (0.001)	−0.002 (0.001)
indus	−0.002 ** (0.001)	−0.002 *** (0.001)
rdjf	−10.669 *** (1.619)	−8.562 *** (1.537)
open	−0.000 ** (0.000)	−0.000 (0.000)
dis	−0.000 (0.000)	−0.000 (0.000)
w×am	0.848 ** (0.363)	0.487 *** (0.714)
w×gdp	0.000 ** (0.000)	0.000 (0.000)
w×urb	0.002 (0.002)	0.006 ** (0.003)
w×indus	−0.004 *** (0.001)	−0.015 *** (0.003)
w×rdjf	2.098 (3.228)	4.179 (5.999)
w×open	−0.000 ** (0.0000540)	−0.000 (0.000119)
w×dis	−0.001 ** (0.000466)	−0.000 (0.000836)
R^2	0.484	0.496
ρ	0.378 *** (0.0513)	0.425 *** (0.0826)

Note: ***, ** and * mean significant at the levels of 1%, 5% and 10%, respectively.

AM had a positive effect on ACEE. The direct term coefficients of AM under the two matrices were 0.397 and 0.506, respectively, and both passed the 10% significance test. This shows that AM has a positive effect on the improvement in ACEE. Among the control variables, the ACEE was positively influenced by the economic development and the urbanization rate, with the disaster's scope considered not significant for the time being; by contrast, industrialization, technological innovation, and the openness of agricultural products had a significant inhibitory effect on ACEE.

The spatial lag-term coefficients of AM under the two matrices were 0.848 and 0.487, indicating that the development of AM had a significant spatial spillover effect on the enhancement of the ACEE. The coefficients of the spatial lag terms of the economic development level and the urbanization rate were both significantly positive, suggesting that the increase in these two variables enhanced ACEE in neighboring provinces. The disaster's scope, the openness of agricultural products, and industrialization all had spatial lag effects with significantly negative coefficients, meaning that the increase in these measures reduced ACEE in the neighboring provinces.

4.3.2. Decomposition of Spatial Spillovers

Due to the existence of spatial lag terms in the SDM, the regression coefficients cannot describe explanatory variables' impact on the explained variables, which could lead to bias in the coefficient estimation. Therefore, we used the variance–covariance matrix of the SDM estimation results [62] to evaluate how each control variable and the core explanatory variables combined to determine ACEE in the local and neighboring regions and categorized the effect into direct and indirect effects.

As can be seen from Table 8, under the 0–1 neighborhood weight matrix, the direct, indirect, and total effects of AM on ACEE all passed the significance test at 5%, indicating that every 1% increase in AM directly increased the ACEE of the province by 0.507% and indirectly increased the ACEE of the neighboring provinces by 1.472%, and the overall region improved by 1.979%. Under the geographic distance weighting matrix, every 1% increase in AM directly contributed to a 0.535% increase in ACEE while indirectly contributing to a 1.146% increase in the ACEE of the neighboring provinces and a 1.682% increase in the ACEE for the entire region. These findings suggest that the interprovincial spillover of AM to ACEE is obviously stronger than the intraprovincial spillover, indicating the spatial spillover of AM to ACEE. Additionally, it reveals the existence of a peer effect.

After comparing the regression results under the two spatial weight matrices, it was found that AM positively affected ACEE in the province under both spatial weight matrices. This may be because the traditional high-carbon-emission production methods have gradually been replaced in the process of AM, due to the dual role of the state and the capital market. This substitution presents new features and technologies in agriculture and improves land output efficiency and labor productivity. In both weight matrices, the indirect effect of AM was also significantly positive, and the indirect effect was much larger than the direct effect, suggesting that while AM rapidly increased, the new features and technologies it provided and the high-quality factors of production spilled over to the neighboring regions, spreading across the region through a "learning effect" and a "trickle-down effect", thus contributing to improving ACEE in neighboring provinces.

Considering the control variables, the total, direct, and indirect effects of economic development on ACEE were significantly positive. It has been shown that the relationship between agricultural resources and the economy has an inverted "U" shape [63]. At present, China's agricultural carbon emissions are at an "inflection point" in the environmental curve, and there is a clear downward trend of agricultural carbon emissions as the agricultural economy develops; the higher the farmers' incomes, the more money they invest in agriculture, improving ACEE, enhancing the region's industrial hierarchy, and rationalizing its industrial structure.

Table 8. Decomposition of SDM model effects under two spatial weight matrices.

Effects	Variables	0–1 Neighborhood Weight Matrix	Geographic Distance Weighting Matrix
Direct effect	am	0.507 ** (2.509)	0.535 *** (2.676)
	gdp	0.000 *** (7.663)	0.000 *** (5.681)
	urb	−0.001 (−0.503)	−0.001 (−1.374)
	indus	−0.002 *** (−3.126)	−0.003 ** (−4.088)
	rdjf	−10.834 *** (−6.452)	−8.536 *** (−5.706)
	open	−0.000 ** (−2.393)	−0.000 (−1.126)
	dis	−0.000 (−0.542)	−0.000 (−0.629)
Indirect effect	am	1.472 *** (2.866)	1.146 *** (0.923)
	gdp	0.000 *** (4.082)	0.000 ** (2.064)
	urb	0.002 (1.026)	0.00835 * (1.894)
	indus	−0.006 *** (−3.496)	−0.027 *** (−4.512)
	rdjf	−2.677 (−0.528)	1.245 (0.117)
	open	−0.000 *** (−2.771)	−0.000 * (−1.666)
	dis	−0.002 ** (−2.2290)	−0.001 (−0.3843)
Total effect	am	1.979 *** (3.7705)	1.682 *** (1.2921)
	gdp	0.000 *** (5.9812)	0.000 *** (2.9303)
	urb	0.002 (0.7855)	0.007 (1.5343)
	indus	−0.008 *** (−4.3348)	−0.029 *** (−4.7445)
	rdjf	−13.512 ** (−2.2208)	−7.291 (−0.6521)
	open	−0.000 *** (−3.0754)	−0.000 * (−1.7424)
	dis	−0.002 ** (−2.1632)	−0.001 (−0.4764)

Note: ***, ** and * mean significant at the levels of 1%, 5% and 10%, respectively.

In the geographic distance weight matrix, the indirect effect of the urbanization rate on the ACEE was significantly positive, suggesting that the growth of urbanization in provinces contributed to a reduction in the scale of agricultural production in the surrounding areas and thus a reduction in carbon emissions. Industrialization had a significant negative effect on the increase in the ACEE because technological innovations resulting from the current rapid pace of industrialization are still oriented toward economic efficiency. As the agricultural economy grows, the demand for input factors increases, creating a "rebound effect" [64]. As the global trade of agricultural products increases, high inputs and consumption will boost agricultural production, which has a significant negative impact on ACEE. The rate of agricultural disasters and ACEE were negatively correlated.

Because of the dependence of agricultural production on the natural environment, disasters will decrease agricultural productivity to a higher extent, leading to a decrease in the ACEE.

4.3.3. Threshold Regression Results

When an economic indicator reaches a specific value, it can cause another indicator to change abruptly, which reflects other forms of development, a phenomenon called the threshold effect. The test results of threshold variables are shown in Table 9, indicating that AM had two thresholds for ACEE, which were 0.3987 and 0.4192, respectively.

Table 9. Threshold test and threshold value (BS count of 300).

	Single Threshold	Double Threshold	Triple Threshold
Threshold value	0.3987 ***	0.4192 ***	0.2028

Note: *** represents the significance at the 1% level.

In Figure 9, the dotted line represents the reference line's 95% significance, and the part of the curve falling under this line indicates the area where the two threshold estimates are equal to the accurate threshold values.

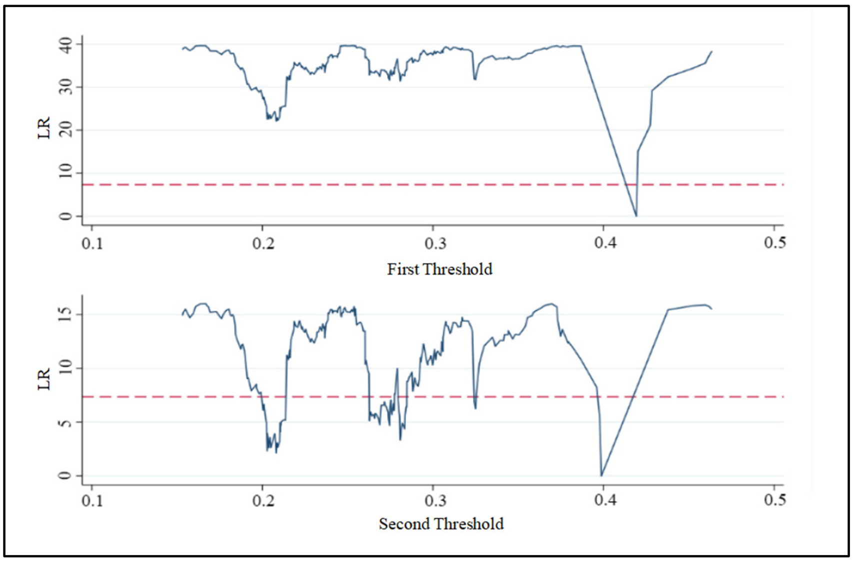

Figure 9. AM threshold values and confidence intervals. Note: the dotted line represents the 95% significance..

Table 10 shows the threshold effect of the core explanatory variables, indicating that agriculture modernization had a nonlinear positive impact on ACEE, with differences in the degree of influence. When the level of AM was lower than 0.3987, the regression coefficient of AM on ACEE was 1.574. When the AM level was between 0.3987 and 0.4192, the regression coefficient was 2.120. When the AM level was higher than 0.4192, the regression coefficient was 1.456, indicating that its impact on enhancing the ACEE decreased.

In dynamic evolution, the marginal effect of AM on improving the ACEE exhibited a decreasing trend. After AM reached the threshold that reflected a shift to a diminishing marginal effect, AM still contributed to ACEE, but it was no longer as influential as at the previous threshold stage.

Considering the control variables, the level of economic development and the urbanization rate had a significant contribution to ACEE, whereas industrialization, technological innovation, the openness of agricultural products, and the disaster's scope had a detrimental impact on ACEE. As the economy grows, more funds are allocated to agriculture, and agricultural production becomes more effective. The increasing rates of the urbanization rate promote the intensification of rural land, increasing the land output rate. Industrialization has provided agriculture with machinery and increased energy consumption, leading to an increase in agricultural carbon emissions. Although technology and R&D investment increases, the transformation of achievements is low. As the trade of agricultural products increases, more products are required, leading to more fertilizer inputs, thus increasing agricultural carbon emissions. Natural disasters have an impact on crops, which reduces the effectiveness of measures aimed at reducing agricultural carbon emissions.

Table 10. Threshold value and parameter estimation.

Variable	Regression Coefficient	T Value
am (am ≤ 0.3987)	1.574 ***	8.20
am (0.3987 < am ≤ 0.4192)	2.120 ***	11.11
am (am > 0.4192)	1.456 ***	9.30
gdp	0.001 ***	11.54
urb	0.005 ***	5.16
indus	−0.004 ***	−5.97
rdjf	−9.098 ***	−5.55
open	−0.174 ***	−3.58
dis	−0.001 **	−2.23
R^2	0.4946	

Note: ***and ** mean significant at the levels of 1% and 5%.

4.3.4. Endogenous Analysis

Since AM and ACEE may be intrinsically related, improvement in AM has a positive contribution to the enhancement of ACEE, and conversely, ACEE will affect the extent of AM advances. Therefore, we selected the most commonly used two-order least-square estimation (2SLS) method using instrumental variables. The lagged one period of the explanatory variable AM was selected as the instrumental variable and 2SLS estimation was used for endogenous analysis. The results are shown in Table 11. The F value of the first stage was 3674.24, which was larger than the critical value, suggesting that there was no weak instrumental variable. The second-stage results are consistent with the previous findings, indicating that reverse causality does not significantly affect the conclusions of this study and that the previous regression results are more reliable.

Table 11. The results of the endogenous analysis.

Variables	(1)	(2)
L_am	0.984 *** (0.011)	
am		1.484 *** (0.139)
gdp	−0.005 (0.005)	0.799 *** (0.060)
urb	0.000 ** (0.000)	0.001 * (0.001)
indus	0.005 (0.006)	−0.728 *** (0.072)
rdjf	0.054 (0.066)	−6.959 *** (0.813)
open	0.003 (0.005)	−0.378 *** (0.056)
dis	−0.000 (0.000)	−0.002 *** (0.000)
_con	0.004 (0.003)	0.232 *** (0.037)
R^2	0.979	0.564
Phase I F value	3674.24	

Note: ***, ** and * mean significant at the levels of 1%, 5% and 10%, respectively.

5. Discussion

5.1. Strategies to Enhance Agricultural Modernization

China has made certain achievements in the agricultural modernization process, but its growth rate is relatively slow, while the regional imbalance phenomenon is prominent, and agricultural modernization in the eastern region is at a higher level, which is in line with the study of Yan [28]. The flat terrain in the eastern region provides a geographical advantage for agricultural production, and the use of e-commerce and digital agriculture technology has been effective in promoting the integration of the agricultural industry [65]. Meanwhile, according to Han [66], the developed regional economy in the eastern region leads to the diversification of its agricultural production methods, which may also be the reason for the higher level of agricultural modernization in the eastern region. In contrast, the central and western regions have backwardness in economic development, agricultural production technology, and management methods, which constrains agricultural modernization. Since agricultural modernization has a promoting effect on carbon emission efficiency in the provinces and neighboring provinces, it is imperative to give full play to the role of regional linkage, with the eastern region actively exploring new modes and paths, while the central and western regions fully discovering their own strengths by learning from successful experiences according to local conditions and enhancing agricultural modernization.

At present, constrained by the dispersal of land parcels, Chinese agriculture is still dominated by the micro-organizational structure of smallholder farming, which makes it difficult to achieve large-scale, industrialized, and intensive management. New agricultural management bodies such as agricultural cooperatives and family farms can enhance the collective action of farmers through the consolidation of resources and the provision of technological and financial support [67], thereby promoting the effective convergence of the smallholder farming economy and agricultural modernization. However, it has also been pointed out that Chinese cooperatives have the problems of shell cooperatives with irregular operation [68,69], which is not conducive to carbon emission reduction, so guaranteed initiatives by the government are crucial to achieving agricultural modernization. In addition, the establishment of a comprehensive agricultural modernization production chain allows for an improvement in the quality, efficiency, and overall competitiveness of agriculture. Increasing the green development level of agricultural modernization; avoiding blind inputs of chemical fertilizers, pesticides, and other means of production; and promoting the use of green farmyard fertilizers are some of the strategies that can be used. These will further restructure the agriculture sector; reduce the scale of cultivation with high energy consumption and crops with high chemical input; allow for adopting new varieties that are low-carbon, high-yielding, and resilient to adversity; and improve plant productivity and carbon sink capacity. To fully acknowledge the significant role that agricultural technology innovation has for agriculture, innovation should be orientated toward "low consumption, low emission, and recycling" and should be developed and applied according to different needs.

5.2. Limitations

The influence mechanism of agricultural modernization on agricultural carbon emission efficiency is more complex, and this research still needs to be deepened. Since agriculture is not only associated with carbon sources but also carbon sinks, we only considered carbon sources; therefore, in future research, we will continue to improve the selection of this indicator system and the influencing factors and establish a scientific and reasonable indicator system for agricultural carbon sinks so that agricultural carbon sources and carbon sinks can be jointly analyzed.

6. Conclusions

Based on the development level of China's agricultural modernization and agricultural carbon emission efficiency from 2000 to 2019, we examined the impact of agricultural modernization on agricultural carbon emission efficiency.

Through the analysis above, it was found that (1) agricultural modernization in the three major regions in China has been developing steadily, but regional differences are widening. In spatial terms, it generally showed a tendency to spread from the eastern coastal areas to the central and western regions, and significant spatial clustering characteristics were observed. (2) China's agricultural carbon emission efficiency continued to increase, although it never reached DEA efficiency, and its overall difference first decreased and then increased. Spatially, the pattern of eastern region > western region > central region was observed, with significant spatial clustering characteristics. (3) Agricultural modernization had a significant promoting effect on carbon emission efficiency. Meanwhile, the direct, indirect, and total effects were all significantly positive, and the indirect effect outweighed the direct effect, indicating that the spatial spillover effect was significant. Between provinces, the spillover effect surpassed the direct effect within a province, demonstrating the peer effect and the trickle-down effect. Agricultural modernization had a nonlinear association with carbon emission efficiency, with a double threshold value, and the marginal effect showed a decreasing trend. After agricultural modernization reached the critical value reflecting a change in trend to a diminishing marginal effect, it still had a promoting effect on carbon emission efficiency, but its influence was not as strong as at the previous threshold stage.

Author Contributions: S.Z.: methodology, validation, writing—original draft preparation, visualization. X.L.: conceptualization, investigation, data curation, methodology, visualization. Z.N.: methodology, validation, visualization. Y.W.: investigation, data curation. D.L.: preparation, writing—original draft preparation. X.C.: conceptualization, project administration. Y.L.: writing—review and editing, funding acquisition. J.P.: conceptualization, formal analysis, supervision, funding acquisition, writing—review and editing. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the National Key R&D Program of China (2018YFC0704702) and the Fundamental Research Funds for the Central Universities (2019jbkyjd014, 2023lzujbkydx034).

Institutional Review Board Statement: Not applicable.

Data Availability Statement: The data used in this study are publicly available, data sources are indicated in the text.

Conflicts of Interest: Authors Xue Li was employed by the company Guangdong Guodi Plannig Science Technology Co., Ltd. The remaining authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest. There is no potential conflict of interest among all authors.

References

1. Ye, S.; Song, C.; Shen, S.; Gao, P.; Cheng, C.; Cheng, F.; Wan, C.; Zhu, D. Spatial pattern of arable land-use intensity in China. *Land Use Policy* **2020**, *99*, 104845. [CrossRef]
2. Yang, H.; Wang, X.; Bin, P. Agriculture carbon-emission reduction and changing factors behind agricultural eco-efficiency growth in China. *J. Clean. Prod.* **2022**, *334*, 130193. [CrossRef]
3. Ito, J.; Li, X. Interplay between China's grain self-sufficiency policy shifts and interregional, intertemporal productivity differences. *Food Policy* **2023**, *117*, 102446. [CrossRef]
4. Huang, J.-k.; Wei, W.; Cui, Q.; Xie, W. The prospects for China's food security and imports: Will China starve the world via imports? *J. Integr. Agric.* **2017**, *16*, 2933–2944. [CrossRef]
5. Wei, H. Structural contradiction and policy transformation of agricultural development in China. *Chin. Rural Econ.* **2017**, *5*, 2. (In Chinese)
6. Tian, Y.; Zhang, J.; Li, B. Research on spatial-temporal characteristics and factor decomposition of agricultural carbon emission based on input angle-taking Hubei Province for example. *Res. Agric. Mod.* **2011**, *32*, 752–755. (In Chinese)
7. Bai, Y.; Deng, X.; Jiang, S.; Zhao, Z.; Miao, Y. Relationship between climate change and low-carbon agricultural production: A case study in Hebei Province, China. *Ecol. Indic.* **2019**, *105*, 438–447. [CrossRef]
8. Gao, P.; Yue, S.; Chen, H. Carbon emission efficiency of China's industry sectors: From the perspective of embodied carbon emissions. *J. Clean. Prod.* **2021**, *283*, 124655. [CrossRef]

9. Liu, Y.; Gan, H.; Wang, D. Analysis of the agricultural modernization level and comparative advantage in Northeast China. *Syst. Sci. Compr. Stud. Agric.* **2005**, *21*, 149–153. (In Chinese)
10. Yang, F. Impact of agricultural modernization on agricultural carbon emissions in China: A study based on the spatial spillover effect. *Environ. Sci. Pollut. Res.* **2023**, *30*, 91300–91314. [CrossRef]
11. Li, J.; Li, S.; Liu, Q.; Ding, J. Agricultural carbon emission efficiency evaluation and influencing factors in Zhejiang province, China. *Front. Environ. Sci.* **2022**, *10*, 1005251. [CrossRef]
12. Han, H.; Zhong, Z.; Guo, Y.; Xi, F.; Liu, S. Coupling and decoupling effects of agricultural carbon emissions in China and their driving factors. *Environ. Sci. Pollut. Res.* **2018**, *25*, 25280–25293. [CrossRef]
13. Du, J.; Liang, L.; Zhu, J. A slacks-based measure of super-efficiency in data envelopment analysis: A comment. *Eur. J. Oper. Res.* **2010**, *204*, 694–697. [CrossRef]
14. Tan, G. Studying Agricultural Modernization Experience of Developed Countries, Managing Six Pairs of Relations in Agricultural Modernization of China. *Res. Agric. Mod.* **2005**, *26*, 62–65. (In Chinese)
15. Diederen, P.; Van Meijl, H.; Wolters, A. Modernisation in agriculture: What makes a farmer adopt an innovation? *Int. J. Agric. Resour. Gov. Ecol.* **2003**, *2*, 328–342. [CrossRef]
16. Liu, D.; Zhu, X.; Wang, Y. China's agricultural green total factor productivity based on carbon emission: An analysis of evolution trend and influencing factors. *J. Clean. Prod.* **2021**, *278*, 123692. [CrossRef]
17. Huang, T.; Xiong, B. Space Comparison of Agricultural Green Growth in Agricultural Modernization: Scale and Quality. *Agriculture* **2022**, *12*, 1067. [CrossRef]
18. Yu, D.; Liu, L.; Gao, S.; Yuan, S.; Shen, Q.; Chen, H. Impact of carbon trading on agricultural green total factor productivity in China. *J. Clean. Prod.* **2022**, *367*, 132789. [CrossRef]
19. Zhang, P.; Yuan, H.; Tian, X. Sustainable development in China: Trends, patterns, and determinants of the "Five Modernizations" in Chinese cities. *J. Clean. Prod.* **2019**, *214*, 685–695. [CrossRef]
20. Liu, Z.; Jia, S.; Wang, Z.; Guo, C.; Niu, Y. A Measurement Model and Empirical Analysis of the Coordinated Development of Rural E-Commerce Logistics and Agricultural Modernization. *Sustainability* **2022**, *14*, 13758. [CrossRef]
21. Peng, C.; Ma, B.; Zhang, C. Poverty alleviation through e-commerce: Village involvement and demonstration policies in rural China. *J. Integr. Agric.* **2021**, *20*, 998–1011. [CrossRef]
22. Carof, M.; Colomb, B.; Aveline, A. A guide for choosing the most appropriate method for multi-criteria assessment of agricultural systems according to decision-makers' expectations. *Agric. Syst.* **2013**, *115*, 51–62. [CrossRef]
23. Zhang, Z.; Li, Y.; Elahi, E.; Wang, Y. Comprehensive Evaluation of Agricultural Modernization Levels. *Sustainability* **2022**, *14*, 5069. [CrossRef]
24. Lobão, M.S.P.; Staduto, J.A.R. Modernização agrícola na Amazônia brasileira. *Rev. De Econ. E Sociol. Rural* **2020**, *58*, e188276. [CrossRef]
25. Kansanga, M.; Andersen, P.; Kpienbaareh, D.; Mason-Renton, S.; Atuoye, K.; Sano, Y.; Antabe, R.; Luginaah, I. Traditional agriculture in transition: Examining the impacts of agricultural modernization on smallholder farming in Ghana under the new Green Revolution. *Int. J. Sustain. Dev. World Ecol.* **2019**, *26*, 11–24. [CrossRef]
26. Xia, M.; Zeng, D.; Huang, Q.; Chen, X. Coupling Coordination and Spatiotemporal Dynamic Evolution between Agricultural Carbon Emissions and Agricultural Modernization in China 2010–2020. *Agriculture* **2022**, *12*, 1809. [CrossRef]
27. Liu, Y.; Li, H.; Ma, H. Evaluation of Agricultural Modernization of State Farms: Based on Entropy Weight Method and TOPSIS Method. *Issues Agric. Econ.* **2021**, *2*, 107–116. (In Chinese)
28. Yan, Z.; Peng, L.; Wu, X. Evaluation System for Agricultural and Rural Modernization in China. *Agriculture* **2023**, *13*, 1930. [CrossRef]
29. Tian, Y.; Huang, J.; An, M. Evaluation on the Efficiency of Agricultural Modernization under the ural evitalization Strategy: Based on the Combined Analysis of Super-fficiency DEA and Comprehensive Entropy Method. *Issues Agric. Econ.* **2021**, 100–113. (In Chinese)
30. Dong, F.; Li, Y.; Gao, Y.; Zhu, J.; Qin, C.; Zhang, X. Energy transition and carbon neutrality: Exploring the non-linear impact of renewable energy development on carbon emission efficiency in developed countries. *Resour. Conserv. Recycl.* **2022**, *177*, 106002. [CrossRef]
31. Mielnik, O.; Goldemberg, J. Communication The evolution of the "carbonization index" in developing countries. *Energy Policy* **1999**, *27*, 307–308. [CrossRef]
32. Wang, R.; Feng, Y. Research on China's agricultural carbon emission efficiency evaluation and regional differentiation based on DEA and Theil models. *Int. J. Environ. Sci. Technol.* **2021**, *18*, 1453–1464. [CrossRef]
33. Syp, A.; Faber, A.; Borzecka-Walker, M.; Osuch, D. Assessment of Greenhouse Gas Emissions in Winter Wheat Farms Using Data Envelopment Analysis Approach. *Pol. J. Environ. Stud.* **2015**, *24*, 2197–2203. [CrossRef] [PubMed]
34. Tengyu, S.; Xia, Y.; Hu, C.; Zhang, S.; Zhang, J.; Xiao, Y.; Fangfang, D. Analysis of regional agricultural carbon emission efficiency and influencing factors: Case study of Hubei Province in China. *PLoS ONE* **2022**, *17*, e0266172.
35. Shu, Q.; Su, Y.; Li, H.; Li, F.; Zhao, Y.; Du, C. Study on the Spatial Structure and Drivers of Agricultural Carbon Emission Efficiency in Belt and Road Initiative Countries. *Sustainability* **2023**, *15*, 10720. [CrossRef]

36. Su, Y.; Ma, H.; Li, F. Xinjiang agriculture and animal husbandry carbon emissions and its decoupling relationship with agricultural economic growth. *Arid Land Geogr.* **2014**, *37*, 1047–1054. (In Chinese)
37. Johnson, J.M.F.; Franzluebbers, A.J.; Weyers, S.L.; Reicosky, D.C. Agricultural opportunities to mitigate greenhouse gas emissions. *Environ. Pollut.* **2007**, *150*, 107–124. [CrossRef] [PubMed]
38. Tian, Y.; Zhang, J.-B.; He, Y.-Y. Research on Spatial-Temporal Characteristics and Driving Factor of Agricultural Carbon Emissions in China. *J. Integr. Agric.* **2014**, *13*, 1393–1403. [CrossRef]
39. MacLeod, M.; Moran, D.; Eory, V.; Rees, R.M.; Barnes, A.; Topp, C.F.E.; Ball, B.; Hoad, S.; Wall, E.; McVittie, A.; et al. Developing greenhouse gas marginal abatement cost curves for agricultural emissions from crops and soils in the UK. *Agric. Syst.* **2010**, *103*, 198–209. [CrossRef]
40. Ye, R.; Qi, Y.; Zhu, W. Impact of Agricultural Industrial Agglomeration on Agricultural Environmental Efficiency in China: A Spatial Econometric Analysis. *Sustainability* **2023**, *15*, 10799. [CrossRef]
41. Xie, H.; Wu, X. Impact and its mechanism of urban- rural integration on the efficiency of agricultural carbon emissions in China. *Resour. Sci.* **2023**, *45*, 48–61. (In Chinese) [CrossRef]
42. Wu, H.; Huang, H.; Chen, W.; Meng, Y. Estimation and spatiotemporal analysis of the carbon-emission efficiency of crop production in China. *J. Clean. Prod.* **2022**, *371*, 133516. [CrossRef]
43. Gong, R.; Xie, L.; Wang, Y. Interactive mechanism and empirical test of agricultural high-quality development and new urbanization. *Reform* **2020**, *7*, 145–159. (In Chinese)
44. Liu, C.; Wang, X.; Bai, Z.; Wang, H.; Li, C. Does Digital Technology Application Promote Carbon Emission Efficiency in Dairy Farms? Evidence from China. *Agriculture* **2023**, *13*, 904. [CrossRef]
45. Bai, L.; Qiao, Q.; Yao, Y.; Guo, J.; Xie, M. Insights on the development progress of National Demonstration eco-industrial parks in China. *J. Clean. Prod.* **2014**, *70*, 4–14. [CrossRef]
46. Tone, K. A slacks-based measure of efficiency in data envelopment analysis. *Eur. J. Oper. Res.* **2001**, *130*, 498–509. [CrossRef]
47. Zhang, J.; Zeng, W.; Wang, J.; Yang, F.; Jiang, H. Regional low-carbon economy efficiency in China: Analysis based on the Super-SBM model with CO_2 emissions. *J. Clean. Prod.* **2017**, *163*, 202–211. [CrossRef]
48. Zhao, Y.; Wang, S.; Zhang, Z.; Liu, Y.; Ahmad, A. Driving factors of carbon emissions embodied in China–US trade: A structural decomposition analysis. *J. Clean. Prod.* **2016**, *131*, 678–689. [CrossRef]
49. Zhang, L.; Pang, J.; Chen, X.; Lu, Z. Carbon emissions, energy consumption and economic growth: Evidence from the agricultural sector of China's main grain-producing areas. *Sci. Total Environ.* **2019**, *665*, 1017–1025. [CrossRef] [PubMed]
50. Li, B.; Zhang, J.; Li, H. Research on Spatial-temporal Characteristics and Affecting Factors Decomposition of Agricultural Carbon Emission in China. *China Popul. Resour. Environ.* **2011**, *21*, 80–86. (In Chinese)
51. Intergovernmental Panel on Climate Change. *Climate Change 2007—Mitigation of Climate Change: Working Group III Contribution to the Fourth Assessment Report of the IPCC*; Cambridge University Press: Cambridge, UK, 2007.
52. Tian, C.; Chen, Y. China's provincial agricultural carbon emissions measurement and low carbonization level evaluation: Based on the application of derivative indicators and TOPSIS. *J. Nat. Resour.* **2021**, *36*, 395. (In Chinese) [CrossRef]
53. Wan, Z.; Liang, J.; Kang, Y.; Fang, W.; Lin, W. Monitoring and Empirical Analysis on Level of Guangdong Province Agricultural Modernization. *Res. Agric. Mod.* **2011**, *32*, 641–645. (In Chinese)
54. Tian, Y.; Lin, Z. Coupling coordination between agricultural carbon emission efficiency and economic growth at provincial level in China. *China Popul. Resour. Environ.* **2022**, *32*, 13–22. (In Chinese)
55. Fu, J.; Li, H. Study on the Spatio-temporal Heterogeneity of Agricultural Water use efficiency and influencing factors in the Yellow River Basin. *Chin. J. Agric. Resour. Reg. Plan.* **2022**, *43*, 77–89. (In Chinese)
56. Tobler, W.R. A Computer Movie Simulating Urban Growth in the Detroit Region. *Econ. Geogr.* **1970**, *46*, 234–240. [CrossRef]
57. Moran, P.A. Notes on continuous stochastic phenomena. *Biometrika* **1950**, *37*, 17–23. [CrossRef] [PubMed]
58. Anselin, L. Local Indicators of Spatial Association—LISA. *Geogr. Anal.* **1995**, *27*, 93–115. [CrossRef]
59. Chang, Y.; Zhang, H.; Shi, B.; Zhang, X. The Dynamic Evolution and Trend Prediction of China's Agricultural Modernization Development Level. *Econ. Probl.* **2022**, *5*, 82–89. (In Chinese)
60. Hansen, B.E. Threshold effects in non-dynamic panels: Estimation, testing, and inference. *J. Econom.* **1999**, *93*, 345–368. [CrossRef]
61. Wang, F.Y.G. Key Issues and Path Selections of Agricultural Green Development in Main Grain Producing Areas. *Chongqing Soc. Sci.* **2022**, *7*, 6–18. (In Chinese)
62. Pace, K.; Lesage, J. Spatial Econometric Modeling of Origin-Destination Flows. *J. Reg. Sci.* **2008**, *48*, 941–967.
63. Yang Liu, S.C. Study on Chinese agaricultural EKC: Evidence from Fertilizer. *Chin. Agric. Sci. Bull.* **2009**, *25*, 263–267. (In Chinese)
64. Yang, L.; Li, Z. Technology advance and the carbon dioxide emission in China—Empirical research based on the rebound effect. *Energy Policy* **2017**, *101*, 150–161. [CrossRef]
65. Hao, H.; Liu, C.; Xin, L. Measurement and Dynamic Trend Research on the Development Level of Rural Industry Integration in China. *Agriculture* **2023**, *13*, 2245. [CrossRef]
66. Han, H.; Lin, H. Patterns of Agricultural Diversification in China and Its Policy Implications for Agricultural Modernization. *Int. J. Environ. Res. Public Health* **2021**, *18*, 4978. [CrossRef] [PubMed]
67. Zhu, X.; Wang, G. Impact of Agricultural Cooperatives on Farmers' Collective Action: A Study Based on the Socio-Ecological System Framework. *Agriculture* **2024**, *14*, 96. [CrossRef]

68. Wang, H.; Qiu, T. The effects of farmer cooperatives on agricultural carbon emissions reduction: Evidence from rural China. *J. Clean. Prod.* **2024**, *450*, 141881. [CrossRef]
69. Zhong, Z.; Jiang, W.; Li, Y. Bridging the gap between smallholders and modern agriculture: Full insight into China's agricultural cooperatives. *J. Rural Stud.* **2023**, *101*, 103037. [CrossRef]