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Can Agricultural Productive Services Inhibit Carbon Emissions? Evidence from China

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Abstract: Reducing agricultural carbon emissions (ACE) is important for the sustainable development of agriculture. Agricultural productive services (APS), a novel form of agricultural technology extension, offer new avenues for promoting sustainable and green agriculture. The present study aims to explore the impact of APS on ACE. In line with the aim of the study, the Kernel density, Moran's I index, spatial Durbin model, and threshold regression model are employed. The findings reveal that APS demonstrate a significant inhibitory effect on ACE, reducing ACE not only within the region itself but also exerting a negative spatial spillover effect on other regions. Furthermore, a non-linear relationship between APS and ACE is observed, characterized by an inverted U-shaped curve with the arable land operating area serving as the threshold. Therefore, to fully harness the inhibitory effect of APS on ACE and to promote environmentally friendly and sustainable agricultural development, policymakers should vigorously develop APS, strengthen regional cooperation, and promote land transfer. Our research can help in understanding the impact of APS on ACE and to promote sustainable agricultural development.

Keywords: agricultural productive services; agricultural carbon emissions; spatial durbin model; threshold effect; sustainable agricultural development

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1. Introduction

Greenhouse gas emissions from human activities are the primary driver of climate change [1]. In China, agricultural activities contribute to 17% of the total greenhouse gas emissions, with CH_4 and N_2O accounting for 50.15% and 92.47% of the total emissions, respectively, which is higher than the global average [2]. Sustainable agricultural development in China has become a growing concern [3]. Reducing agricultural carbon emissions (ACE) is not only a key issue to address for sustainable agricultural development [4] but also an integral part of achieving the dual carbon goals [5]. China's agricultural development is currently undergoing a critical transition from quantitative expansion to qualitative improvement, necessitating a balanced approach to agricultural development and ACE reduction [6]. Restraining high-carbon practices in agricultural production activities and promoting the development of low-carbon industries are crucial measures for reducing ACE [7]. Agricultural productive services (APS), also known as services outsourcing, refers to the outsourcing of some or all aspects of agricultural production to service organizations or other farmers. APS play an intermediate role in pre-production, production, and post-production activities in agriculture, offering a wide range of services. These services include guidance on the supply and use of inputs such as fertilizers, pesticides, and mulch; technology support in areas such as soil formula fertilization, pest prevention and control; and mechanization services such as irrigation and tillage [8]. As a new form of agricultural technology extension and industry, APS present new possibilities for mitigating ACE [9]. The Chinese government recognizes the significance of developing the APS system. In

2008, the Third Plenary Session of the 17th Party Central Committee proposed the establishment of a new type of agricultural production social services system. In 2014, the No. 1 Document of the Central Government reiterated the need to improve the social services system of agricultural production. In 2017, the Ministry of Agriculture issued the Notice on Supporting the Work of Agricultural Production Social Services and the Guidance on Accelerating the Development of Agricultural Production Services, emphasizing the promotion of green agricultural development and sustainable resource utilization. As a result of these policies, agricultural production social services, represented by APS, have experienced rapid growth [10]. From 2005 to 2020, the output value of APS in China increased from CNY 112.78 billion to CNY 720.98 billion, with an average annual growth rate of 12.97%. The proportion of APS' output value in the overall output value of agriculture, forestry, animal husbandry, and fishery rose from 2.86% to 5.10%. Therefore, it is crucial to effectively measure the impact and spatial spillover effect of APS on ACE and to identify key threshold variables.

Currently, research on ACE has primarily focused on two aspects: (1) ACE measurement. Compared with industrial carbon emissions, ACE measurement methods are more diverse, including emissions factor methods, model methods, and life cycle methods [11]. Among these, the emissions factor method is widely applied and favored by many scholars [12]. West et al. developed an ACE measurement system that considers fertilizer, pesticide, irrigation, and seeding practices [13]. Dong et al. analyzed greenhouse gas emissions from rice cultivation and livestock farming [2]. Li et al. introduced the concept and calculation method of ACE in China [14]. Based on the calculation of total ACE, researchers have investigated regional differences and the spatial and temporal evolution characteristics of ACE. The results have shown significant regional disparities in ACE across China [15]. The growth trend of total ACE has become more evident, stabilizing or even slightly decreasing over time [16,17], exhibiting an overall inverted U-shaped pattern [18]. (2) Factors influencing ACE. Existing studies have primarily examined agricultural economic development, population size, technological progress, resources and the environment, production methods, and policy systems. Agricultural economic growth and population increase significantly contribute to agricultural carbon emissions [19]. Technological advancements in agriculture are also essential factors affecting ACE, with studies showing that technological advancements can substantially reduce ACE [20]. Zhao et al. found that provinces with high soil–water compatibility performed better in reducing ACE [21]. Green production practices such as deep tillage, no-till seeding, and straw return can effectively reduce ACE [22,23]. Carbon-emissions-trading pilot policies, reasonable agricultural subsidy policies, and carbon sinks are also effective measures for ACE reduction [24–26].

Research on APS has mainly focused on two aspects. One is the impact of APS on agricultural production. APS serve as a substitute for family labor, effectively reducing the time and cost of agricultural production [27] and enabling farmers to increase their income through non-farm activities [28]. Furthermore, APS have a positive effect on improving the level of agricultural output [29]. The adoption of APS can increase agricultural productivity among Chinese farmers by 25.61% [30]. The other aspect is the effect of APS on the agricultural environment. Xu et al. (2022) indicated that APS enhance agricultural green total factor productivity, with a particularly significant effect in the eastern region [31]. Li et al. also confirmed the positive effect of APS on agricultural green total factor productivity using microscopic data [32]. Regarding specific service types, fertilizer application services and pest control services are crucial for enhancing the environmental sustainability of agriculture [33]. Zhang et al. (2023) highlighted that APS reduce fertilizer application through the moderating effects of plot size and off-farm labor employment [34]. Ji (2018) concluded that APS significantly reduce pesticide use and enhance pesticide abuse prevention and control [35]. Zhu et al. (2022) concluded that APS effectively improve agro-environmental efficiency by optimizing the input–output structure [36].

Although existing studies provide valuable references for further expanding and improving the understanding of ACE, there is limited discussion on the effects of APS on ACE. Few studies have directly focused on the effects of APS on ACE. Additionally, the "cross-area operation" nature of APS has been neglected, leading to an underestimation of the spatial spillover effect of APS in reducing ACE [37]. Can APS effectively suppress ACE? Do APS affect ACE in other regions? These questions require further investigation. Therefore, this paper aims to analyze the spatial and temporal evolution pattern of ACE using provincial panel data from mainland China. The study employs a spatial Durbin model to explore the impact of APS on ACE and utilizes a threshold model to examine the nonlinear relationship between APS and ACE.

This paper contributes to three main aspects. First, in terms of research methodology, given the cross-regional flows and spatial spillover effects of APS, this paper adopts a spatial Durbin model to investigate whether APS influences ACE in other regions from a spatial perspective. Second, in terms of research perspective, most of the existing literature on APS utilizes micro-level data for empirical analysis, whereas this paper empirically examines the impact of APS on ACE using Chinese provincial macro-level panel data. Finally, in terms of research content, this paper incorporates the arable land operation area into the analytical framework, enabling an analysis of the nonlinear impact of APS on ACE and exploring the nonlinear relationship between the two using a threshold model.

The remainder of this paper is organized as follows. Section 2 presents an analysis of the concepts and theories related to ACE and APS. Section 3 describes the study design, including the research methodology, variable selection, and data sources. Section 4 presents and analyzes the main findings. Section 5 provides further discussion. Section 6 summarizes the main conclusions.

2. Concept Definition and Research Hypothesis

2.1. Concept Definition

The academic community currently lacks a clear understanding of the scope and boundaries of APS. To address this issue, it is necessary to define these. This paper defines APS based on the ratio of the output value of productive services in agriculture, forestry, animal husbandry, and fishery to the total output value of these sectors. The productive services in agriculture, forestry, animal husbandry, and fishery encompass various support activities related to their production, which are closely related to APS. Data from recent years are available to support the concepts and contents of APS [38]. Compared with other industries, ACE originate from diverse sources, including carbon emissions due to agricultural land use activities, greenhouse gas emissions from crop growth and development, and gases and waste released from ruminant farming [39,40]. Among these sources, agricultural land use activities are the primary contributors to ACE [41], and analyzing carbon emissions from this sector provides valuable insights. Therefore, in this paper, ACE mainly refers to carbon emissions resulting from agricultural land use activities. Four main aspects contribute to carbon emissions in agricultural land use activities: (1) carbon emissions caused by chemical inputs such as fertilizers, pesticides, and agricultural films; (2) carbon emissions from the consumption of fossil fuels in agricultural machinery operations; (3) indirect fossil fuel consumption through electricity used for irrigation; and (4) soil organic carbon loss due to tillage. However, ACE is an aggregate concept that does not fully capture its harmonious relationship with agricultural development. Hence, to emphasize the connection between ACE and agricultural economic performance, this paper uses agricultural carbon intensity as a measure of ACE. Agricultural carbon intensity refers to the carbon emissions resulting from the value added per unit of agricultural output [42].

2.2. Research Hypothesis

The rational smallholder theory of farmer behavior posits that farmers, as rational economic agents, prioritize profit maximization [43]. Consequently, they tend to intensively use agrochemical inputs in pursuit of higher yields, leading to increased levels of ACE.

According to the externality theory, ACE generate negative externalities, and farmers do not bear the full costs of these externalities. As a result, they lack sufficient incentives to adopt green production practices that reduce agricultural carbon emissions. Schultz argues that transforming traditional agriculture requires modern agricultural inputs, which are costly and risky and may crowd out farmers' incentives for green production. APS can alleviate the cost burden of purchasing agricultural equipment and facilitate the introduction of advanced technologies, management concepts, and human capital into agricultural production [44]. By adopting input-use guidance services, farmers can promote the rational use of chemical substances such as pesticides and fertilizers. Soil testing and fertilizer application services enable precise fertilization, while mechanical deep-plowing services ensure the effective protection of arable land quality. These green production practices contribute to carbon emissions control in agricultural production and enhance agrochemical use efficiency [45,46]. Based on the above analysis, this paper proposes the first research hypothesis.

Hypothesis 1: *APS have a negative effect on ACE.*

Spatial econometrics suggests that the geographic characteristics and economic attributes of one region are correlated with the same characteristics and attributes of neighboring regions. Consequently, ACE in one region may have an impact on ACE in other regions. Similarly, APS may also influence ACE in neighboring regions due to their cross-regional operations. The vast size of China and the distinct differences in crop production cycles between regions provide ample opportunities for cross-regional APS operations. For instance, agricultural machinery services can provide tillage, seeding, and harvesting services to other regions [47], affecting the allocation of production factors, planting structures, and technological progress in neighboring regions. Based on the above analysis, this paper proposes the second research hypothesis.

Hypothesis 2: *APS have a negative spatial spillover effect on ACE.*

In China, agriculture is predominantly composed of smallholder operations, with more than 80% of farmers cultivating land areas smaller than 0.56 hectares [48]. The fragmented nature of these small landholdings hampers agricultural machinery operations [49], resulting in reduced operational efficiency and increased fuel consumption, which contributes to carbon emissions. APS can enhance the concentration of land plots and promote land-scale operations, which improve the efficiency of agricultural machinery and reduce use of fuel. In addition, with the expansion of land-scale operations, the probability of a reasonable amount of fertilizer inputs for farmers increases significantly [50]. Consequently, the effect of APS in reducing ACE is influenced by the size of the cultivated land under operation. Based on the above analysis, this paper proposes the third research hypothesis.

Hypothesis 3: *The effect of APS on ACE is nonlinear and is based on the size of the cultivated land under operation as a threshold.*

Therefore, this paper aims to depict the spatio-temporal evolution pattern of ACE based on provincial panel data from mainland China. The spatial Durbin model will be employed to explore the effect of APS on ACE. Furthermore, a threshold model will be used to verify the nonlinear relationship between APS and ACE. The main framework is illustrated in Figure 1.

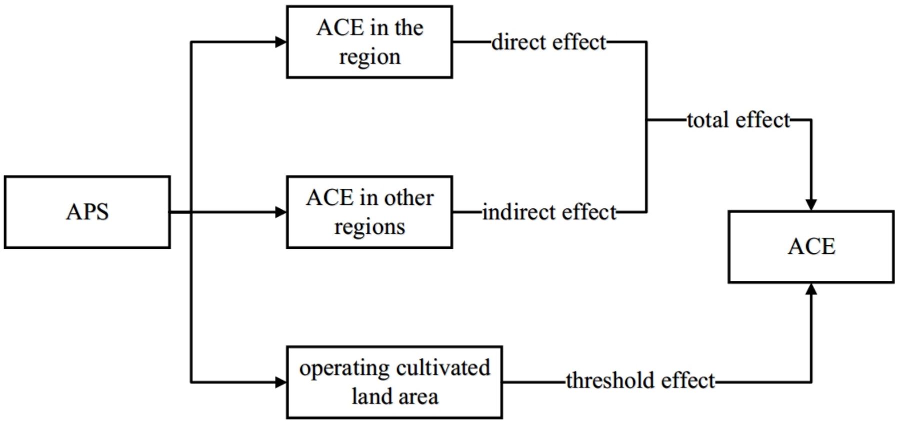

Figure 1. Main framework of the empirical study.

3. Materials and Methods

3.1. Research Methodology

3.1.1. Kernel Density Analysis Method

The kernel density analysis method is a commonly employed nonparametric estimation technique. It utilizes data and smoothed estimation to measure the distribution pattern of random variables and provides robust estimates of probability densities [51]. By applying this method, the dynamic evolutionary trend of ACE can be elucidated using a functional form:

$$f(x) = \frac{1}{nh}\sum_{i=1}^{n} k\left(\frac{x_i - x}{h}\right) \tag{1}$$

where n is the sample size, h is the bandwidth, x_i is the ACE in region i, and $k(\cdot)$ is the kernel function. In this paper, the Epanechnikov kernel function and the Silverman optimal bandwidth are selected to estimate the dynamic evolution of ACE.

3.1.2. Spatial Weight Matrix Setting

Before conducting spatial measurements, it is necessary to establish the spatial relationship among the research objects, which involves determining whether provinces and cities share the same geographical boundaries or if their geographical distances fall within a certain range. In this paper, the Rook contiguity criterion is adopted to construct the neighboring spatial weight matrix, denoted as W_{ij}. This matrix captures and defines the spatial proximity and relationship between locations, allowing for the characterization of relative geographic location in space:

$$W_{ij} = \begin{cases} 1 \cdots\cdots i \text{ is adjacent to } j \\ 0 \cdots\cdots i \text{ is not adjacent to } j \end{cases} \tag{2}$$

where all diagonal elements of the matrix take $W_{ij} = 0$.

3.1.3. Global Spatial Autocorrelation

The global spatial autocorrelation index is employed to assess the spatial correlation of variables at the overall level, with the widely used test statistic being the global Moran's index. In this study, the global Moran's I index, as proposed by Anselin, is utilized to analyze the global spatial evolution characteristics of ACE and APS. The calculation of the global Moran's I index is as follows [52]:

$$Moran's\ I = \frac{n\sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij}(x_i - \bar{x})(x_j - \bar{x})}{\sum_{i=1}^{n}\sum_{j=1}^{n}\sum_{i=1}^{n} W_{ij}(x_i - \bar{x})^2} = \frac{\sum_{i=1}^{n}\sum_{j\neq 1}^{n} W_{ij}(x_i - \bar{x})(x_j - \bar{x})}{S^2\sum_{i=1}^{n}\sum_{j\neq 1}^{n} W_{ij}} \tag{3}$$

where n is the sample size; x_i, x_j are the variables of spatial locations i and j, respectively, and the spatial weights W_{ij} indicate the proximity of spatial locations i and j. The global Moran's I index takes values in the range $[-1, 1]$, and values between $(0, 1]$ imply a positive correlation, values between $[-1, 0)$ imply a negative correlation, and values of 0 imply no spatial autocorrelation.

3.1.4. Spatial Durbin Model Specification

Spatial econometric analysis commonly utilizes three models: the spatial lag model (SLM), spatial error model (SEM), and spatial Durbin model (SDM). These models can be transformed into each other under certain conditions. The SDM, which incorporates lagged terms for both the independent and dependent variables, allows for the unbiased estimation of coefficients in either the spatial lag or spatial error form during data production, without affecting potential spatial spillover effects.

To determine whether the spatial econometric model outperforms the traditional panel regression model, several tests are conducted. These include the spatial error LM test, spatial error Robust LM test, spatial lag LM test, and spatial lag Robust LM test. If each test is successfully passed, this indicates that the spatial econometric model performs better than the traditional panel regression model. Additionally, the LR degeneracy test and Wald test are conducted. If the original hypothesis can be significantly rejected, it implies that the SDM cannot degenerate into SLM or SEM [53]. Based on this, this paper first constructs the SDM model and then performs a series of tests to determine whether a specific form of the spatial lag model or spatial error model should be utilized [54]. The model is specified as follows:

$$Y_{it} = \beta_0 + \rho \sum_{j=1}^{n} W_{ij} Y_{it} + \theta X_{it} + \varphi \sum_{j=1}^{n} W_{ij} X_{ij} + \alpha_i + \delta_t + \varepsilon_{it} \tag{4}$$

where Y_{it} denotes the observed value of the explanatory variable in period t in region i, Y_{jt} denotes the observed value of the explanatory variable in period t in region j, X_{it} is the observed value of the explanatory variable in period t in region i, X_{jt} denotes the observed value of the explanatory variable in period t in region j, W_{ij} is an element of the adjacency weight matrix, ρ is the spatial regression coefficient of the explanatory variable, θ is the regression coefficient of the explanatory variable when spatial effects are not considered, φ is the spatial regression coefficient of the explanatory and control variables, α_i denotes a spatial fixed effect, δ_t is a time fixed effect, and ε is a spatial autocorrelation error term.

3.1.5. Spatial Spillover Effect Specification

Estimating spatial spillover effects using point estimates from traditional spatial regression models can lead to misleading conclusions [55]. Therefore, this study employs the partial differential estimation method to estimate the direct, indirect, and total effects of APS on ACE [56]. The direct effect quantifies the average impact of the independent variable on the dependent variable within the same region, while the indirect effect quantifies the average impact of the independent variable on the dependent variable in other regions and the total effect quantifies the average impact of the independent variable on the dependent variable across all regions. The underlying spatial Durbin model is reformulated in the following vector form [57]:

$$(I_n - \rho W)Y = al_n + \theta X + \varphi W X + \varepsilon \tag{5}$$

Further expansion of this yields:

$$Y = \sum_{r=1}^{k} S_r W X_r + V W a l_n + V W \varepsilon \tag{6}$$

or, more specifically,

$$\begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{bmatrix} = \sum_{r=1}^{k} \begin{bmatrix} S_r W_{11} & S_r W_{12} & \cdots & S_r W_{1n} \\ S_r W_{21} & S_r W_{22} & \cdots & S_r W_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ S_r W_{n1} & \cdots & \cdots & S_r W_{nn} \end{bmatrix} \begin{bmatrix} x_{1r} \\ x_{2r} \\ \vdots \\ x_{nr} \end{bmatrix} + VWal_n + VW\varepsilon \tag{7}$$

where the direct effect, indirect effect, and total effect are obtained by taking the partial derivatives of the dependent variable with respect to the independent variable [58].

3.1.6. Threshold Effect Specification

In this study, we adopt Hansen's panel regression model [59] to explore the threshold effect. The explanatory variable is the ACE, the core explanatory variable is the APS, and the threshold variable is the scale of farmland operation. We construct a threshold regression model using the following equation:

$$\begin{aligned} ACE = \omega_i + \alpha_1 Control + \beta_1 APS \cdot D(Area < \theta_1) + \beta_2 APS \cdot D(\theta_1 < Area < \theta_2) \\ + \cdots\cdots + \beta_n APS \cdot D(\theta_{n-1} < Area < \theta_n) \\ + \beta_{n+1} APSD(Area > \theta_n) + \mu_{it} \end{aligned} \tag{8}$$

where $\theta_1, \theta_2, \ldots, \theta_n$ denote the threshold values at n different levels, *Control* denotes the control variable, $D(\cdot)$ is the indicator function, and μ_{it} is the random disturbance term.

3.2. Variable Selection

The core explanatory variable in this study is the APS, which is characterized by the ratio of the output value of agriculture, forestry, animal husbandry, and fishery production services to the total output value of agriculture, forestry, animal husbandry, and fishery. ACE serves as the explanatory variable and its calculation is based on the following formulas [15,60,61]:

$$ACE = \frac{\sum E_i \times T_i}{AAGDP} \tag{9}$$

where E_i is the input quantity of each type of agricultural carbon source and T_i is the carbon emissions coefficient of each type of agricultural carbon source, as shown in Table 1.

Table 1. Calculation coefficient and sources of ACE.

Carbon Source	Coefficient Source	Emissions Coefficient
Fertilizer	Oak Ridge National Laboratory, United States	0.8956 kg/kg
Pesticides	Oak Ridge National Laboratory, United States	4.9341 kg/kg
Agricultural film	Intergovernmental Panel on Climate Change	5.1800 kg/kg
Diesel	Intergovernmental Panel on Climate Change	0.5927 kg/kg
Tillage	College of Agronomy and Biotechnology, China Agricultural University	312.6000 kg/hm^2
Irrigation	Rural Development Research Center of Hubei	20.4760 kg/hm^2

As for the control variables, this study includes the following variables for control purposes. The urbanization level (*Urban*) is represented by the ratio of the urban population to the total population at the end of the year. Damage to agriculture (*Damage*) is measured by the ratio of the affected agricultural area to the total cultivated area. The share of food crops (*Grain*) is calculated as the ratio of the area sown with food crops to the total cropped area. Agricultural structure (*Structure*) represents the proportion of agricultural output in the overall output of agriculture, forestry, animal husbandry, and fishery. The development of agriculture (*Develop*) is indicated by the ratio of agricultural output value to the rural population. Support (*Support*) is the expenditure on agriculture, forestry, and water affairs.

Education (*Education*) is measured as the average number of years of education for the rural population and is computed as follows:

$$Education = \frac{no + primary \times 6 + junior \times 9 + senior \times 12 + college \times 15}{all} \quad (10)$$

where *no* represents the number of people who have not attended school, *primary* represents the number of people in elementary school, *junior* represents the number of people in middle school, *senior* represents the number of people in high school, *college* represents the number of people in college and above, and *all* represent the number of people over 6 years old.

Regarding the threshold variable, the area of cultivated land under family contract operation (*Area*) is employed to capture the extent of land under operation. The area of arable land under family contract operation, as defined by the Ministry of Agriculture, pertains to the land contracted by farmers in rural collective economic organizations. It encompasses land that is collectively owned by rural communities or owned by the state but collectively utilized by farmers through family contracts.

3.3. Data Sources

This paper takes 31 provinces in mainland China as the study area. The original data for the APS comes from the China Tertiary Industry Statistical Yearbook, which has a specific statistical subject called the output value of productive services in agriculture, forestry, animal husbandry and fishery. The data for fertilizer dosage, pesticide dosage, agricultural film dosage, diesel dosage, and agricultural irrigation area are collected based on the actual figures for the respective year. However, data specifically about tillage are not directly available in the statistics. To address this, this paper employs crop-sowing area as a proxy for tillage. All the aforementioned data are sourced from the China Rural Statistical Yearbook. Data on grain, damage to agriculture, development, and support are obtained from the China Rural Statistical Yearbook. Information regarding the agricultural structure is sourced from the China Statistical Yearbook. Data on the urban population, total population at the end of the year, and the years of education of the rural population are obtained from the China Population and Employment Statistical Yearbook. The data on the area of arable land under operation are derived from the China Rural Management Statistics Annual Report (excluding Tibet). To mitigate heteroskedasticity and to address inconsistencies in data magnitudes that could bias the estimation results, the ACE, Develop, Support, Education, and Area variables in the model are transformed using logarithms. The descriptive statistics for each variable are presented in Table 2.

Table 2. Descriptive statistics of variables.

Variable	Unit	Mean	Std. Error	Min	Max
Explained variable					
ACE	Million tons/Billion ¥	−1.310	0.699	−3.185	0.491
Core explanatory variable					
APS	-	0.119	0.080	0.022	0.537
Control variables					
Urban	-	0.542	0.174	0.209	0.896
Damage	-	0.199	0.148	0.000	0.940
Grain	-	0.663	0.136	0.355	0.971
Structure	-	0.518	0.086	0.302	0.746
Develop	Billion CNY/10,000 people	−0.451	1.515	−4.783	2.934
Support	Million CNY	6.417	0.436	4.984	7.127
Education	Year	1.999	0.133	1.175	2.268
Threshold variable					
Area	hm^2	1.148	1.040	0.956	1.246

4. Results and Analysis

4.1. Spatial and Temporal Evolution of ACE

In this study, we employed kernel density estimation to analyze the temporal evolution of ACE from 2005 to 2020. Using Stata 16.0 software, we generated the kernel density curve for national agricultural carbon emissions (Figure 2). The horizontal axis represents ACE, while the vertical axis represents kernel density. Over the examination period, the kernel density distribution curve of ACE generally exhibited a rightward shift, a decrease in peak magnitude, and an increase in horizontal width. These observations indicate a weakening trend in ACE and an increase in regional disparity. In comparison with 2005, the curve shape in 2010 did not change significantly, but the center of the density function shifted to the right, and the peak decreased, indicating a decrease in ACE during this period. Furthermore, compared with 2010, the center of the density function in 2015 continued to shift rightward, the wave peak further declined, and the double-peak pattern evolved into a single-peak pattern. ACE continued to decrease during this phase. Lastly, when comparing 2015 with 2020, the center of the density function was seen to have shifted leftward, the peak had slightly increased, and the range of change had significantly widened. ACE intensified during this phase, and the inter-provincial gap widened. A possible reason for this is that the "Pesticide and Chemical Fertilizer Reduction Action" policy in 2015 had effectively reduced ACE, but the differences in the evolution of industrial structure and the level of agricultural modernization in each region led to significant differences at the regional levels [15,62].

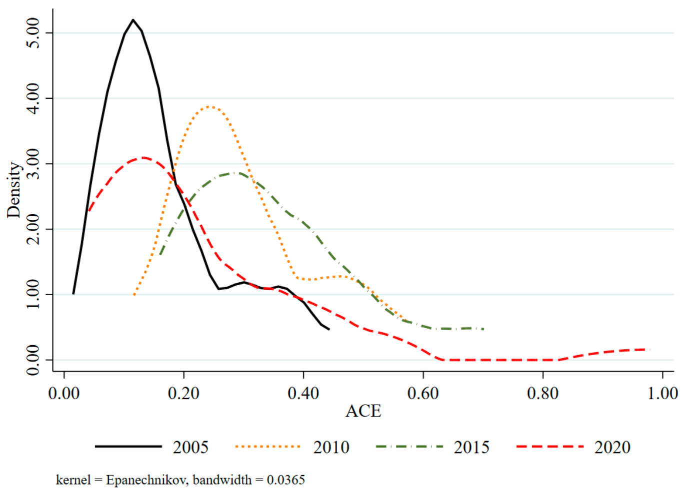

Figure 2. Kernel density analysis of ACE.

To provide a detailed characterization of the spatial and temporal evolution of ACE, this study used ArcGIS 10.8 software to classify the raw data into three classes according to the proportion of ACE in each province to the whole country: low intensity (<2%), medium intensity (2–4%) and high intensity (>4%). Figure 3 shows the spatial and temporal evolution trends of ACE in each province. From the spatial perspective, the ACE of each province show obvious non-equilibrium and heterogeneity. Low-intensity, medium-intensity, and high-intensity areas all show obvious clustering characteristics. The low-intensity areas are mainly concentrated in the Sichuan and Chongqing regions and extend to the middle and lower reaches of the Yangtze River. The medium-intensity areas continue to contract from the arid northwest and central regions to the eastern regions. The high-intensity areas show an obvious trend of migration from the southeast coast to the central region and then to the north. To sum up, the ACE show more and more obvious spatial clustering characteristics.

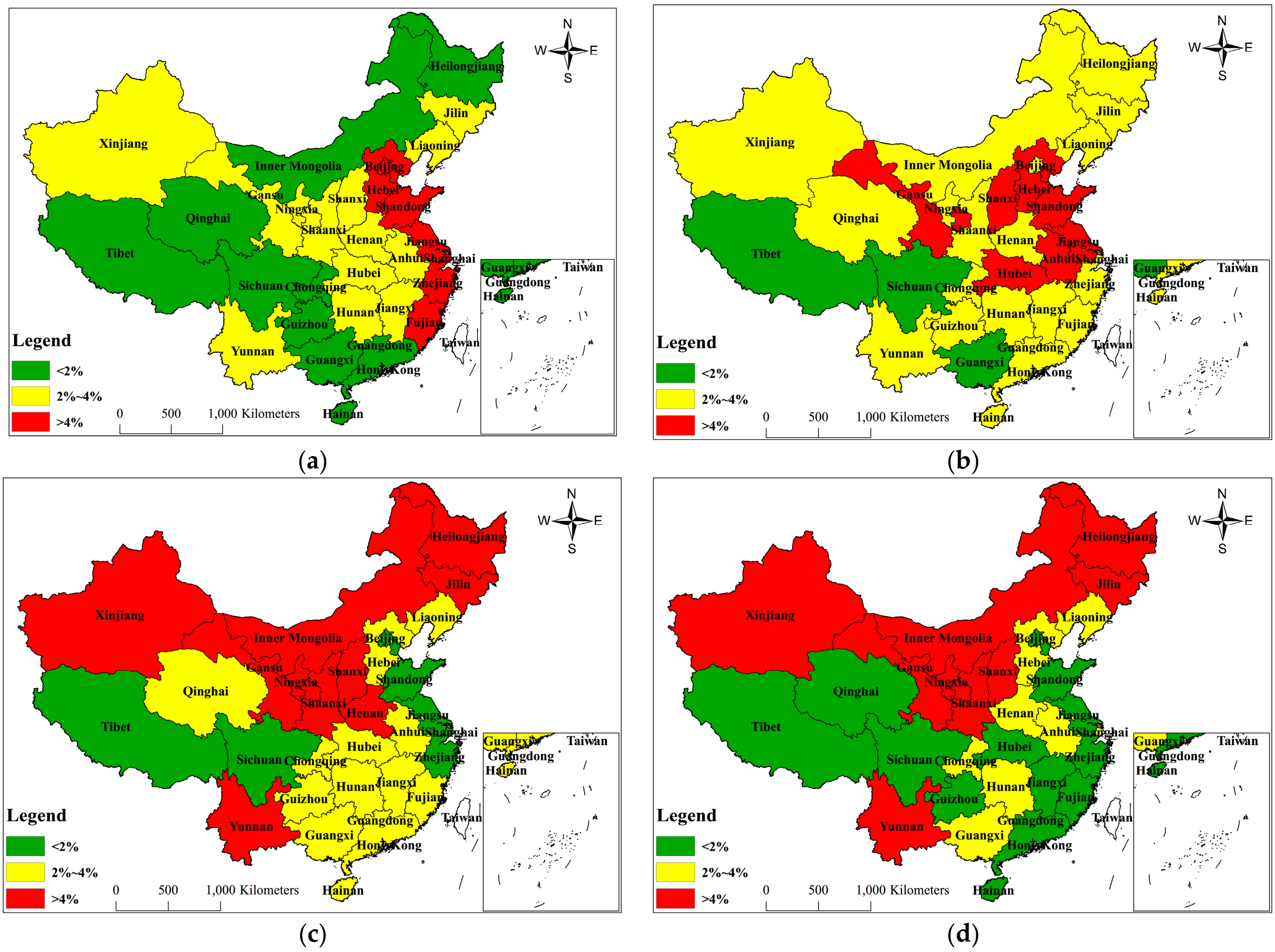

Figure 3. Temporal evolution trend of ACE. (**a**) 2000; (**b**) 2005; (**c**) 2010; (**d**) 2020.

4.2. Spatial Correlation of ACE and APS

In this study, the global Moran's I indices for ACE and APS were calculated separately using Stata 16.0 software, and the results are presented in Figure 4. The positive Moran's I indices for ACE indicate a significant spatial clustering distribution, with relatively stable spatial correlation fluctuations. Similarly, Moran's I index for APS demonstrates a fluctuating growth trend, suggesting a strengthening spatial agglomeration distribution of APS. The observed trends in ACE and APS indicate a potential spatial correlation between the two variables, warranting further analysis using a spatial econometric model.

The data used in this paper are short panel data, meaning that the time is shorter than the number of entities. As a result, there is no need to consider the unit root problem, and all variables are assumed to be smooth series by default [63]. To ensure reliable results, it is important to address any multicollinearity among the variables that may affect the research outcomes. In this paper, the variance inflation factor (VIF) test is employed to examine multicollinearity. The results presented in Table 3 indicate that the maximum VIF value among the variables is 3.300, which is below 10. Additionally, the mean VIF value of 2.250 is greater than 1 but less than 5, satisfying the conditions for the absence of severe multicollinearity. Consequently, there is no significant multicollinearity among the variables considered in this paper, allowing for further empirical testing.

In this paper, the selection of the appropriate spatial econometric model to analyze the influencing factors of ACE is guided by the principles of "from specific to general" and "from general to specific" [64]. The results are presented in Table 4.

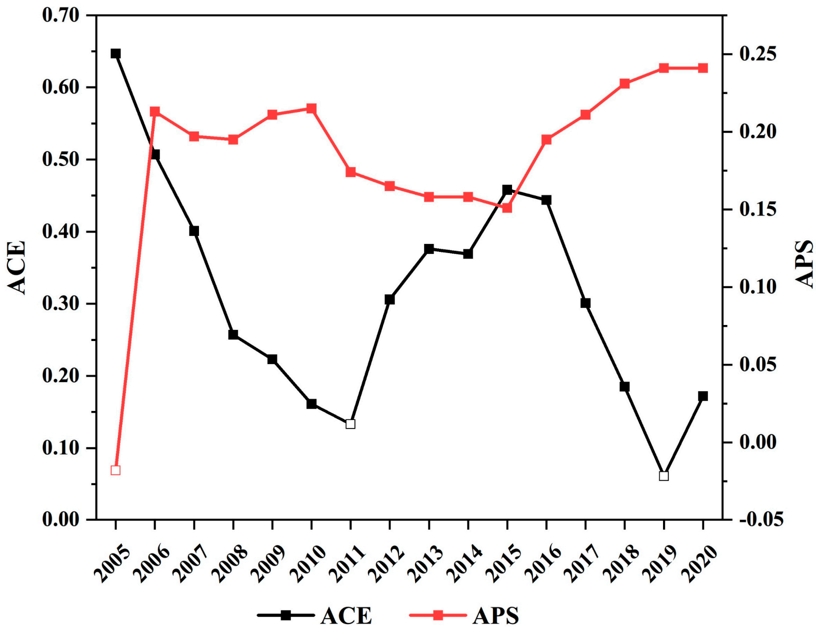

Figure 4. Moran's I index for ACE and APS. Note: significance tests at the 5% level were passed at the solid points.

Table 3. VIF test results.

Variable	*Service*	*Urban*	*Damage*	*Grain*
VIF	3.110	3.070	1.430	1.060
Variable	*Structure*	*Develop*	*Support*	*Education*
VIF	1.510	1.790	3.300	2.770

Table 4. Correlation tests for model selection.

Test Method	Test Name	Test Statistic
F-test	F-Test	42.150 ***
LM test	LM–Error	183.364 ***
	LM–Error Robust	53.472 ***
	LM–Lag	155.343 ***
	LM–Lag Robust	25.451 ***
LR test	LR–Both–Ind	52.890 ***
	LR–Both–Time	291.160 ***
	LR–SDM–SEM	32.810 ***
	LR–SDM–SLM	63.090 ***
Wald test	Wald–SDM–SEM	32.860 ***
	Wald–SDM–SLM	62.520 ***
Hausman test	Hausman	51.830 ***

Note: *** indicates passing the significance test at the 1% level.

The LM–Error, LM–Error Robust, LM–Lag, and LM–Lag Robust tests all pass the 1% significance level, indicating the presence of spatial error effects and spatial lag effects. The existence of spatial effects introduces complexity to the relationship between variables, and using the traditional OLS model may lead to biased estimation. Therefore, a panel regression model that incorporates spatial factors is necessary [65].

Next, the Hausman test significantly rejects the null hypothesis at the 1% significance level, suggesting that the fixed-effects model outperforms the random-effects model when considering the specific characteristics of the study sample. Furthermore, the LR–Both–Ind and LR–Both–Time tests both pass the 1% significance level, indicating that the SDM with two-way fixed effects should be used.

Finally, tests were conducted to determine whether the SDM could be degraded to SEM or SLM. The LR–SDM–SEM and LR–SDM–SLM tests are both significant at the 1% significance level, indicating that SDM is the optimal choice. The results of the Wald–SDM–SEM and Wald–SDM–SLM tests also suggest that SDM does not degenerate into SEM or SLM. In conclusion, based on these tests, the two-way fixed-effect SDM model was selected to analyze the influencing factors of agricultural carbon emissions intensity in this paper.

In Table 5, the estimation results of the two-way fixed-effect SDM model and the OLS model are presented. In the two-way fixed-effect SDM model, the spatial autoregressive coefficient ρ is estimated to be 0.340 and passes the test at the 1% significance level. This indicates the presence of a positive spillover effect of ACE. Specifically, a 1% increase in the carbon emissions intensity of neighboring provinces will lead to a 0.340% increase in the ACE of the province under consideration. This suggests that there is a significant interaction and intensification of ACE between regions. It is important to note that the estimation results of the OLS model are provided for reference. The OLS model does not account for spatial effects and may suffer from biased estimation when spatial dependence is present. The inclusion of spatial factors in the two-way fixed-effect SDM model helps to capture the spatial spillover effects and provides more reliable estimates of the relationships between variables.

Table 5. Estimated results of the effect of APS on ACE.

	OLS Model		**Two-Way Fixed Effects SDM Model**	
	Coefficient	**Std. Error**	**Coefficient**	**Std. Error**
Main effect				
APS	−4.596 ***	0.539	−5.283 ***	0.538
Urban	−0.657 **	0.290	−2.222 ***	0.789
Damage	0.524 ***	0.197	0.412 ***	0.146
Grain	0.662 ***	0.184	−3.142 ***	0.463
Structure	4.823 ***	0.346	2.024 ***	0.548
Develop	−0.025	0.021	0.009	0.016
Support	−0.157	0.101	0.443 *	0.264
Education	1.303 ***	0.305	−0.973 *	0.543
Constants	−5.059 ***	0.684		
Spatial effect				
Wx APS			−3.413 ***	1.088
Wx Urban			1.211	1.603
Wx Damage			−0.515 **	0.266
Wx Grain			−2.756 ***	0.863
Wx Structure			1.107	1.103
Wx Develop			−0.041	0.036
Wx Support			−1.548 ***	0.490
Wx Education			−2.391 **	1.186
ρ			0.340 ***	0.054
σ^2			0.090 ***	0.006

Note: ***, **, * denote passing the significance test at 1%, 5%, and 10% levels, respectively.

4.3. Impact of APS on ACE and Spatial Spillover Effect

Due to the presence of the spatial lag term in the SDM model, estimating the impact solely based on the estimated parameters may lead to biased results. Therefore, it is necessary to decompose the total effects of each explanatory variable into direct and indirect effects, taking into account the spatial spillover effects and the variance–covariance matrix of the estimated results [66]. The decomposition results of the total effects, direct effects, and indirect effects of each explanatory variable in the two-way fixed-effect SDM model are presented in Table 6.

Table 6. Decomposition of the spatial effects of two-way fixed-effect SDM.

Variables	Direct Effect	Indirect Effect	Total Effect
APS	−5.746 *** (0.527)	−7.477 *** (1.211)	−13.222 *** (1.209)
Urban	−2.197 *** (0.743)	0.795 (2.152)	−1.401 (2.265)
Damage	0.390 *** (0.141)	−0.559 (0.353)	−0.169 (0.394)
Grain	−3.500 *** (0.449)	−5.468 *** (1.227)	−8.969 *** (1.355)
Structure	2.190 *** (0.555)	2.516 (1.655)	4.706 ** (1.946)
Develop	0.007 (0.018)	−0.050 (0.054)	−0.043 (0.065)
Support	0.310 (0.286)	−2.049 *** (0.699)	−1.739 ** (0.847)
Education	−1.239 ** (0.525)	−3.841 ** (1.768)	−5.080 *** (1.984)

Note: *** and ** indicate passing significance tests at the 1% and 5% levels, respectively. Standard errors are in parentheses.

According to the results in Table 6, the direct and indirect effects of APS, the core explanatory variable, on ACE are both significantly negative at the 1% level. However, the coefficient of the indirect effect is larger, indicating that APS not only reduces ACE in the local area but also suppresses ACE in other areas. For every 1% increase in APS, ACE decreases by 13.222%, with a 5.746% decrease locally and a 7.477% decrease in other areas. This can be attributed to the improved service form and capacity of APS, which regulate agricultural production behavior locally and drive agricultural green development in other regions through cross-area operations, thereby suppressing ACE [67]. Hence, hypotheses 1 and 2 are verified.

As for the control variables, the direct and indirect effects of food-crop share and years of education on ACE are significantly negative. This implies that an increase in food-crop share and years of education not only reduces ACE in the local area but also drives other areas to reduce ACE. For every 1% increase in food-crop share, ACE decreases by 8.969%, with a 3.500% decrease locally and a 5.468% decrease in other areas. This can be explained by the higher carbon sink capacity of food crops, which helps to lower ACE. Additionally, for every 1% increase in years of education, ACE decreases by 5.080%, with a 1.239% decrease locally and a 3.841% decrease in other areas. This suggests that higher education levels promote the adoption of scientific management practices and advanced green production techniques, leading to a reduction in carbon source consumption.

On the other hand, the direct effects of agricultural damage and agricultural structure on ACE are both significant at the 1% level, with coefficients of 0.390 and 2.190, respectively. However, their indirect effects are not significant, indicating that these factors exacerbate ACE in the local region but do not have a significant effect on ACE in neighboring areas [15].

Regarding the degree of agricultural support, its indirect effect on ACE is −2.049 and passes the significance test at the 1% level. This suggests that an increase in the level of agricultural support does not significantly affect ACE in the local region but can reduce ACE in neighboring regions [68].

4.4. Robustness Test

To ensure the reliability of the estimation results, this paper adopts two ways of replacing the core explanatory variables and replacing the weight matrix for robustness testing. First, the adjacency matrix is replaced with the geographic distance matrix, which is constructed as follows:

$$W_{ij} = \begin{cases} \frac{1}{d^2} \cdots\cdots i = j \\ 0 \cdots\cdots i \neq j \end{cases} \quad (11)$$

where d is the distance between regions i and j.

Second, the logarithm of the output value of productive services (*lnSer*) is used to replace the original core explanatory variable. In Table 7, both models show that the estimated spatial autoregressive coefficient (ρ) is positive and significant at the 1% level. This confirms the presence of positive spatial spillover effects in ACE, indicating that an increase in ACE in neighboring provinces leads to an increase in ACE in the focal province. These results are consistent with the original estimation results, providing robustness to the findings.

Table 7. Robustness test of SDM.

Replace Core Explanatory Variables				Replace Weight Matrix			
Main Effect		Spatial Effect		Main Effect		Spatial Effect	
lnSer	−1.653 *** (0.067)	*Wx* *lnSer*	0.008 (0.205)	*APS*	−6.264 *** (0.498)	*Wx* *APS*	−6.445 *** (1.466)
Urban	−0.361 (0.682)	*Wx* *Urban*	4.939 *** (1.483)	*Urban*	−1.588 * (0.897)	*Wx* *Urban*	1.535 (1.948)
Damage	0.044 (0.116)	*Wx* *Damage*	−0.080 (0.265)	*Damage*	0.248 * (0.151)	*Wx* *Damage*	−0.117 (0.347)
Grain	−0.531 (0.392)	*Wx* *Grain*	−0.063 (0.746)	*Grain*	−3.240 *** (0.499)	*Wx* *Grain*	−3.425 *** (0.974)
Structure	−0.810 * (0.434)	*Wx* *Structure*	−0.373 (1.067)	*Structure*	1.935 *** (0.571)	*Wx* *Structure*	2.517 * (1.399)
Develop	0.003 (0.013)	*Wx* *Develop*	−0.018 (0.036)	*Develop*	0.001 (0.017)	*Wx* *Develop*	−0.008 (0.046)
Support	0.055 (0.211)	*Wx* *Support*	−1.478 ** (0.638)	*Support*	0.223 (0.276)	*Wx* *Support*	−3.580 *** (0.835)
Education	0.289 (0.439)	*Wx* *Education*	−0.655 (1.321)	*Education*	−0.892 * (0.565)	*Wx* *Education*	−7.643 *** (1.703)
ρ		0.408 *** (0.066)		ρ		0.284 *** (0.070)	
σ^2		0.057 *** (0.004)		σ^2		0.097 *** (0.006)	

Note: ***, **, * indicate significance at the 1%, 5%, and 10% levels, respectively. Standard errors are in parentheses.

In Table 8, after decomposing the total, direct, and spillover effects of each explanatory variable based on the variance–covariance matrix of the estimation results, the direct and indirect effects of APS on ACE are also significantly negative. This indicates that APS not only reduce ACE in this region but also reduce ACE in other regions, showing significant negative spatial spillover, which is consistent with the original estimation results. In summary, the results of both robustness tests prove that the original estimation results are reliable.

Table 8. Robustness tests of spatial spillover effects.

Variables	Replace Core Explanatory Variable			Replace Weight Matrix		
	Direct Effect	Indirect Effect	Total Effect	Direct Effect	Indirect Effect	Total Effect
APS	−1.705 *** (0.068)	−1.099 *** (0.262)	−2.804 *** (0.274)	−6.685 *** (0.499)	−11.216 *** (1.856)	−17.902 *** (1.920)
Urban	0.013 (0.625)	7.994 *** (2.347)	8.008 *** (2.320)	−1.552 * (0.829)	1.658 (2.477)	0.105 (2.372)
Damage	0.049 (0.112)	−0.120 (0.405)	−0.070 (0.435)	0.258 * (0.144)	−0.089 (0.442)	0.170 (0.466)

Table 8. *Cont.*

Variables	Replace Core Explanatory Variable			Replace Weight Matrix		
	Direct Effect	Indirect Effect	Total Effect	Direct Effect	Indirect Effect	Total Effect
Grain	−0.557 (0.407)	−0.407 (1.355)	−0.965 (1.567)	−3.474 *** (0.487)	−5.903 *** (1.421)	−9.377 *** (1.596)
Structure	−0.867 * (0.450)	−1.275 (1.821)	−2.142 (2.037)	2.100 *** (0.555)	4.091 ** (1.985)	6.191 *** (2.179)
Develop	0.003 (0.014)	−0.023 (0.063)	−0.020 (0.072)	0.002 (0.018)	−0.006 (0.067)	−0.004 (0.078)
Support	−0.070 (0.240)	−2.463 ** (1.122)	−2.533 ** (1.245)	0.030 (0.300)	−4.871 *** (1.230)	−4.840 *** (1.367)
Education	0.230 (0.431)	−0.858 (2.251)	−0.628 (2.421)	−1.333 ** (0.535)	−10.760 *** (2.532)	−12.093 *** (2.686)

Note: ***, **, * indicate passing significance tests at the 1%, 5%, and 10% levels, respectively. Standard errors are in parentheses.

5. Discussion

5.1. Threshold Effect Based on the Scale of Arable Land Operation

China's agricultural sector is predominantly composed of smallholder operations, with over 80% of farmers working on arable land areas smaller than 0.04 hm^2 [48]. The performance of APS is closely tied to the scale of arable land operation. For instance, once the cultivated area reaches a certain size, it facilitates the smooth operation of farm machinery [49]. A small cultivated area presents challenges in achieving machinery substitution for labor and results in increased production costs. Additionally, a limited arable area can lead to issues with uneven or irregular usage of chemical inputs. Consequently, the impact of APS on ACE may exhibit clear non-linear characteristics. In other words, the effect of APS on ACE may undergo transitive or abrupt changes as the scale of arable land operation increases, rather than being a simple linear progression.

To advance this study, we employed the research concept of threshold regression to test the threshold effect of the model and to determine the threshold value. The determination of the number of thresholds and the identification of threshold effects were conducted by repeatedly sampling 300 times using the Bootstrap method in the Stata 16.0 software (Table 9). The results revealed that the model did not meet the criteria for double- and triple-threshold tests, while a single threshold was statistically significant at the 5% level. Hence, the area of the cultivated land operation emerged as the threshold variable influencing the relationship between APS and ACE. Furthermore, the relationship between APS and ACE demonstrated a nonlinear pattern, with the area of cultivated land operation acting as the sole threshold.

Table 9. Results of the threshold effect test.

Threshold Test	F Statistic	Bootstrap Times	Boundary Value		
			10%	5%	0%
Single threshold	49.130 **	300	34.532	44.594	50.168
Double threshold	21.330	300	43.863	60.797	76.830
Triple threshold	15.290	300	34.409	39.912	50.345

Note: ** indicates passing significance test at 5% level.

The regression results from the threshold model (Table 10) reveal that the threshold value is 15.394. When the cultivated operating area is below 1.026 hm^2, the effect of APS on ACE is 4.415, and it passes the significance test at the 5% level. This indicates that APS intensifies ACE at various sample intervals. Specifically, a 1% increase in APS leads to a 4.415% increase in ACE. Conversely, when the cultivated operating area exceeds 1.026 hm^2, the effect of APS on ACE is −8.247, and it passes the significance test at the 1% level. This suggests that APS reduce ACE at different sample intervals. For every 1% increase in APS, ACE decrease by 8.247%. Therefore, the relationship between APS and ACE is non-linear, demonstrating the presence of a threshold.

Table 10. Regression results of the threshold model.

Variables	Coefficient	Std. Error	T Value	95% Confidence Interval
APS ($Area < 1.026$)	4.415 **	2.051	2.150	[0.384, 8.445]
APS ($Area \geq 1.026$)	−8.247 ***	0.593	−13.910	[−9.411, −7.082]
Control variables			Controlled	
Observations			480	
F			69.110 ***	

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

Furthermore, based on the relationship between the size of the arable land-operation area and the threshold value, this study divides the provinces into two groups, high-value areas and low-value areas, above and below the threshold value, respectively. This division is depicted in Figure 5.

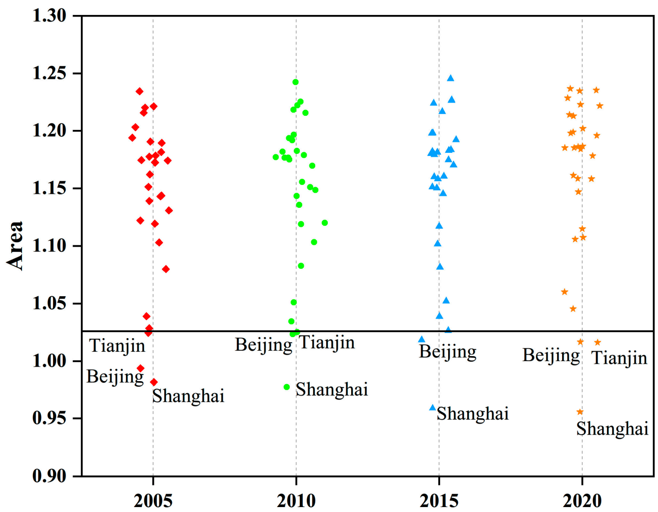

Figure 5. Comparison of cultivated land operating area and threshold by province.

The majority of provinces fall within the high-value area, where the advancement of APS has a suppressive effect on ACE. Conversely, Beijing, Tianjin, and Shanghai are classified as part of the low-value area, where an increase in APS levels corresponds to higher ACE. In summary, the relationship between APS and ACE exhibits an inverted U-shaped non-linear pattern as the scale of arable land operation expands. Therefore, hypothesis 3 has been confirmed.

5.2. Implications for China

Based on the results of the empirical study, the following implications are concluded in this paper to further develop APS and reduce ACE. First, APS should be vigorously developed. The government should increase support for APS development, improve top-level design and support for APS, and make up for the shortage of resources and systems that restrict APS development. The government should build a scientific and reasonable APS policy system, expand the scale of APS development, and optimize the structure of APS development. Second, regional cooperation should be strengthened, and a development policy with a global perspective should be formulated. The government should focus on promoting regional cooperation and expanding the scope of APS services. This includes establishing an information platform for integrated cross-regional APS to facilitate the rational flow and scientific allocation of service resources between regions.

Third, land transfer should be accelerated to promote the scale operation of arable land. As the most important factor of production, land must be transferred to make full use of it. The government should establish rural land transfer service agencies, build a platform for rural land transfer at all levels, and increase publicity and guidance on rural land transfer. This will accelerate the full flow of unemployed arable land, avoid arable land abandonment and idleness, and promote the effective allocation of land and other resources.

5.3. Shortcomings and Prospects

The concept of APS encompasses a wide range of services [69], and the impact of different services on ACE exhibits heterogeneity. For instance, agricultural machinery services consume significant amounts of fossil fuels and contribute to greenhouse gas emissions, thereby exacerbating ACE [70]. Conversely, services such as soil testing and fertilization, sprinkler and drip irrigation, and straw return have the potential to effectively reduce agricultural surface-source pollution and decrease ACE [48]. Consequently, the impact of APS on ACE is a complex issue. In this paper, the study examines the impact of APS on ACE and spatial spillover effects from a broad perspective, without undertaking a detailed decomposition of each service type. Moreover, the focus of this study is primarily on the plantation industry, without considering the heterogeneous characteristics of the livestock, forestry, and fishery sectors. This highlights a potential avenue for future research. Further investigations can be conducted using micro-level research data to delve deeper into these aspects [71].

6. Conclusions

This paper utilizes Chinese provincial panel data from 2005 to 2020 to examine the spatial and temporal evolution characteristics of ACE. It constructs a spatial Durbin model to investigate the direct impact and spatial spillover effect of APS on ACE, and further employs a threshold regression model to analyze the nonlinear relationship between APS and ACE. Based on the findings, corresponding policy recommendations are proposed. The specific research results are summarized as follows.

Kernel density analysis reveals that the distribution curve of ACE generally exhibits a rightward trend, with a decrease in the peak and a transition from a double peak to a single peak. The horizontal width of the distribution increases, indicating a weakening trend in ACE and an expansion of regional disparity. Further analysis indicates that the low-intensity areas are mainly concentrated in the Sichuan and Chongqing regions and extend to the middle and lower reaches of the Yangtze River. The medium-intensity areas continue to contract from the arid northwest and central regions to the eastern regions. The high-intensity areas show an obvious trend of migration from the southeast coast to the central region and then to the north.

The results of the spatial Durbin model demonstrate that APS have a significant inhibitory effect on ACE. They not only reduce ACE within the local area but also exert a negative spatial spillover effect on other areas. A 1% increase in APS leads to a 13.222% decrease in ACE, comprising a 5.746% local decrease and a 7.477% decrease in other areas.

The threshold regression model reveals an inverted U-shaped nonlinear relationship between APS and ACE, with a threshold arable land operation size of 1.026 hm^2. When the arable land operation size is below 1.026 hm^2, APS exacerbate ACE. Conversely, when the arable land operation size exceeds 1.026 hm^2, APS suppress ACE.

To fully leverage the inhibitory effect of APS on ACE, this paper puts forward three policy recommendations. First, there is a need to vigorously develop APS and to enhance the APS service system. Second, regional cooperation should be strengthened. Third, efforts should continue to promote provincial land transfer and enhance the marketability of land transfer.

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