agriculture

MDPI

Article

Towards Sustainable Development: The Impact of Agricultural Productive Services on China's Low-Carbon Agricultural Transformation

Ning Geng [1], Xiaoqing Zheng [2], Xibing Han [1] and Xiaonan Li [3,*]

[1] School of Public Administration, Shandong Normal University, Jinan 250014, China; gengning@sdnu.edu.cn (N.G.)
[2] Inspur Smart City Technology Co., Ltd., Jinan 250014, China; zhengxq@inspur.com
[3] School of Business, Shandong Normal University, Jinan 250014, China
* Correspondence: lixiaonan@sdnu.edu.cn

Abstract: In the context of carbon neutrality, the low-carbon transition in agriculture is crucial to achieving carbon mitigation through clean production. The provision of agricultural productive services (APS) is pivotal for modernizing farming practices in China. However, the impact of this on the low-carbon transformation has received limited attention. This research examined the non-linear relationship between agricultural productive services and low-carbon development, including verifying a threshold effect with APS as the threshold variable, employing panel data for 31 provinces in China from 2010 to 2021. The results of the study suggested that the effect of services associated with agricultural productivity on the transition of the agricultural sector to low-carbon practices varied across threshold ranges. Specifically, when the APS exceeded the threshold of 2.4396, a significant suppressive effect was observed on carbon emission intensity. Further analysis revealed that APS indirectly influenced the farmland scale and agricultural technological advancements, thereby promoting the low-carbon transition of China's agriculture. Based on these results, it is recommended to intensify the development of APS in key cereal-producing regions, while emphasizing the harmonious progress of these services in conjunction with large-scale farmland management.

Keywords: agricultural productive service; low-carbon transition; agricultural carbon emissions; China

check for updates

Citation: Geng, N.; Zheng, X.; Han, X.; Li, X. Towards Sustainable Development: The Impact of Agricultural Productive Services on China's Low-Carbon Agricultural Transformation. *Agriculture* **2024**, *14*, 1033. https://doi.org/10.3390/agriculture14071033

Academic Editors: Maria Pergola and Cornelia Flora

Received: 16 April 2024
Revised: 15 June 2024
Accepted: 25 June 2024
Published: 28 June 2024

1. Introduction

Global climate change has led to a series of effects on food security, human activities, and the long-term development of economic and social systems, offering a common problem for nations globally [1,2]. Scholars have increasingly recognized significant emissions of greenhouse gases, specifically CO_2, CH_4, and N_2O, as crucial factors in the phenomenon of global warming [3]. The UNFCC was officially executed in March 1994 as a response to these challenges. Legislative initiatives on a global scale to control greenhouse gas emissions commenced with the ratification and implementation of the Kyoto Protocol and the Paris Agreement. It is mandatory for all signatory countries, regardless of their level of development, to commit to emission reduction targets and ensure they meet the associated responsibilities. The IPCC recommended in 2018 that to stabilize the climate, the world should aim to attain net zero global emissions of greenhouse gases by about 2050. The endorsement resulted in the extensive implementation of the "carbon neutrality" objective. It is believed that a low-carbon transition is essential to achieving carbon reduction and sustainable production [4].

China plays an active role in global climate governance and provides support as an initial signatory to the UNFCC. The country consistently improves its autonomous contributions to this cause. In 2015, China announced new autonomous emission reduction goals, aiming for a 60–65% reduction in carbon emissions by 2030 compared to 2005 levels (China has just announced its post-2020 climate target: to reduce carbon emission intensity by 60% to 65% based on 2005 levels, http://www.tanjiaoyi.com/article-10949-1.html (accessed on 20 December 2023)). The Chinese government introduced new approaches and strategies in tackling climate change by formally announcing the "dual carbon" objectives in 2020 ("carbon peak" before 2030 and "carbon neutrality" before 2060, Source: "Xi Jinping's Speech at the General Debate of the 75th Session of the United Nations General Assembly (Full Text)" https://www.gov.cn/xinwen/2021-09/22/content_5638597.htm (accessed on 20 December 2023)).

Carbon emission reduction serves as the basis for achieving the "dual carbon" objectives, which also require increased carbon sequestration. Agricultural practices also contribute significantly to the global release of carbon, although industry, manufacturing, and the energy sector are the primary contributors to carbon emission reduction [5,6]. According to a 2019 UNFCCC report, the agricultural sector, in combination with food systems, contributes to an estimated 31% of global carbon emissions caused by human activities. Based on data provided by the FAO, greenhouse gas emissions associated with worldwide agricultural operations and food production increased by 17% in 2019 relative to 1990 levels [7]. China, being the leading global emitter of CO_2, exhibits an upward trend in agricultural carbon emissions, which account for 16–17% of its total emissions. This figure exceeds the global average and continues to rise [8]. Energy consumption is expected to play a significant role in the capital-intensive nature of modern agricultural development for the foreseeable future, putting China's efforts to reduce agricultural carbon emissions under immense pressure.

To address the pressing difficulties, it is crucial to promptly address carbon emissions from farming and promote the adoption of sustainable, low-emission agricultural practices. Higher carbon emissions from agriculture in China can be attributed directly to inefficient resource utilization and production practices [9,10]. Currently, there are 230 million farming households in China, each with an average arable land area of 7.8 mu (approximately 0.52 hectares). Among these households, 210 million handle less than 10 mu (around 0.67 hectares) of arable land (data come from the National Bureau of Statistics in China. http://www.stats.gov.cn (accessed on 20 December 2023)). The environmental improvement resulting from the reduction of agricultural carbon emissions (ACEs) is an excellent public benefit [9], accompanied by evident externalities [11]. In addition to technical and higher cost constraints, profit-maximizing "rational peasants" [12] encounter limits such as transaction costs, human capital, and technology dissemination. These constraints not only hinder their active adoption of low-carbon ways but also make it difficult for them to receive direct economic benefits [13]. However, the smallholder economy in China possesses organizational benefits and the capacity to specialize in labor. Agricultural production processes are becoming more divided, allowing for the outsourcing of various tasks, including sowing, seedling cultivation, fertilization, pest management, harvesting, and drying, to service organizations. According to Qian [14], the shift from a "self-management" paradigm to "outsourced service management" can stimulate the innate motivation for adopting sustainable, low-carbon agricultural practices, as proposed by Qing [15]. Agricultural productive services (APS) are crucial in promoting the transition to low-carbon agriculture (LCA) within this framework. APS accomplishes this by incorporating environmentally friendly components such as biomass-derived pesticides, sustainable fertilizers, and biodegradable agricultural films. Additionally, it utilizes advanced low-carbon technologies that encompass accurate soil analysis, targeted fertilization methods, eco-friendly pest control, and systems for reintroducing crop residues to the soil [16,17]. As a result, the focus of our research is to elucidate the mechanisms by which APS influences the low-carbon transformation of Chinese agriculture (LCTA) and to provide empirical evidence to support this claim.

2. Literature Review and Analytical Framework

2.1. A Review of the Multiple Impacts of APS on LCTA

Recently, there has been a substantial increase in studies focusing on long-term, low-emission growth in the agricultural sector. Previous studies on LCA have mostly focused on the following aspects: (1) Calculation of ACEs and structural characteristics: Researchers have dedicated efforts to the measurement of ACEs and the comprehension of their structural properties [18–20]. (2) Evaluating the feasibility of agricultural carbon emission reduction, [21] made an approximation of the worldwide potential to reduce agricultural greenhouse gases (AGHGs) as early as 1997. However, the results were unreliable due to inadequate baseline data on land use and AGHGs. Subsequent research on agricultural carbon reduction utilized the concept of shadow pricing, originally derived from economics, to assess the expenses associated with environmental pollution control [22]. Additionally, it explored regional variations in cost reduction [1,23], establishing a foundation for further investigation in this field. (3) Identifying the driving factors behind ACEs, Important factors include the level of economic development in agriculture [24], improvements in agricultural management techniques [25,26], technological advancements in agriculture [27], effective utilization of land resources [28], and the consumption of LCA products [29]. (4) Selecting pathways for LCTA and formulating supportive policies: This includes efficient planting methods, organic agriculture, and agricultural biogas [30,31], conservation tillage techniques such as no-till or crop residue return [2], and strategies to improve soil carbon sequestration [32]. Countries have implemented a range of approaches to encourage LCA, including the imposition of carbon emission taxes [33] and the establishment of carbon credit trading markets within the farming sector [34,35]. In summary, although considerable research has been conducted on LCTA thus far, there is still a lack of literature on the correlation between APS and LCTA.

The notion that efficiency is increased through labor division is a fundamental principle in economic theory and was first proposed by Smith in 1776. Currently, APS plays a vital role in promoting agricultural techniques in China, making a substantial contribution to the modernization of the sector [36,37]. APS covers the provision of funds, technological progress, machinery, and services associated with the processing and promotion of agricultural products at different phases of production. On a fundamental level, APS promotes specialization and labor division within the agricultural domain [38,39]. The LCTA model is influenced by the specific factor endowments of a nation or region in practical application. Agriculture in developed countries, such as the United States, tends to substitute mechanical capital input for labor input. The literature focuses mostly on the effect of farming scale on ACEs [40], emphasizing that larger operations and higher mechanization levels are more likely to provide economies of scale [41]. Meanwhile, countries like Japan and South Korea, which have high population densities and limited land, frequently utilize intensive low-carbon technological solutions to counteract the scarcity of arable land. This approach promotes sustainable low-carbon farming practices [42]. China also faces the imbalance of having a large population and limited land. The yield-targeted agriculture strategy, which involves the heavy application of chemicals, has effectively tackled food security concerns for China's population of over 1.4 billion [43]. However, the continuous and excessive application of agricultural chemicals has caused a significant crisis in resources and the environment, leading to increased greenhouse gas emissions. This poses a threat to the quality and safety of agricultural products, as demonstrated by occurrences such as the contamination of rice with cadmium [5]. To enhance the LCTA, APS facilitates the reduction of fertilizers by modifying the composition of capital, labor, and technology inputs [15]. Furthermore, they effectively overcome the invisible scale limitations of biochemical technologies (e.g., pesticides, fertilizers) and permit the continuous operation of agriculture [44,45].

Furthermore, numerous scholarly investigations have examined the potential of APS to improve the output of LCA. These factors encompass the improvement of eco-friendly efficiency in grain crops [11], the increase in crop production [46], the rise in income for agricultural producers [45], and the upgrading of the agricultural sector's capacity to meet demand [47]. Carbon emission intensity is an important measure for evaluating the performance of low-carbon agricultural production. It helps to balance the goals of stabilizing atmospheric CO_2 levels and promoting economic growth. Additionally, it serves as a standard for assessing the effectiveness of efforts to mitigate climate change [48]. Considering environmental costs within the global value chain, including service elements in manufacturing, might reduce the carbon emission intensity of exports by promoting factor reallocation and technical developments [49]. Moreover, studies utilizing the World Input-Output Database (WIOD) transnational panel data suggest that China's transition to a service-oriented manufacturing sector had a greater effect on decreasing the intensity of ACEs compared to similar transformations in developed economies [50].

The investigations mentioned above have made contributions to the LCTA and LCTA. Unfortunately, in the context of small-scale farming, research on how APS affects LCA via multiple pathways and mechanisms is limited. Thus, based on previous research, we have carried out both theoretical and empirical investigations to examine the influence of APS on LCTA. The following are key directions for expanded research and detailed study: (1) Developing a conceptual model to clarify how APS affects LCTA and its fundamental rational processes; (2) utilizing time-series cross-sectional data spanning 2000 to 2021 from China's 31 provinces (in view of the availability of data, panel data for 31 provinces of China (excluding Taiwan Province, Hong Kong, and Macao SAR) were selected, including municipalities and districts), to empirically assess the complex relationship between APS and the decrease of ACEs, specifically examining the presence of a threshold effect with APS acting as the pivotal variable; and (3) delving into the various channels APS may employ to exert influence on LCTA. The results from our study are expected to contribute to the formulation of LCAT strategies and the refinement of carbon emission mitigation policies.

2.2. Theoretical Perspectives of the Impacts of APS on LCTA

Expanding upon previous understandings of the inherent connection between scale and economy, economists claim that endogenous economic development originates from the division of labor [51–53]. Pa-nayotou (1993) provided additional evidence regarding the interaction between economic growth and environmental pollution by illustrating how aggregate pollutant emissions (including sulfur dioxide, carbon dioxide, and particulate matter) and economic growth exhibit an inverse U-shaped pattern over time; this relationship is referred to as the environmental Kuznets curve (EKC). Recent studies indicate that economic growth has a significant influence on ecological and environmental changes through three specific mechanisms: scale effects, technological advancements, and adjustments in economic structure [54]. Given the distinct framework of rural land ownership in China, which distinguishes between ownership, contractual rights, and operational rights, and taking into account the influence of external resource allocation and the ability to separate different stages of farming, it is feasible to incorporate APS as an innovative component of various stages of agricultural production. This integration may involve the implementation of advanced machinery, organic fertilizers, and sustainable technologies, which would promote further specialization and division within the agricultural sector [36,55]. Therefore, this would lead to the transformation of conventional high-carbon agriculture practices in China. This study tries to analyze the underlying logic of how APS contributes to the transition towards low-carbon farming practices, as discussed in the aforementioned theories (Figure 1).

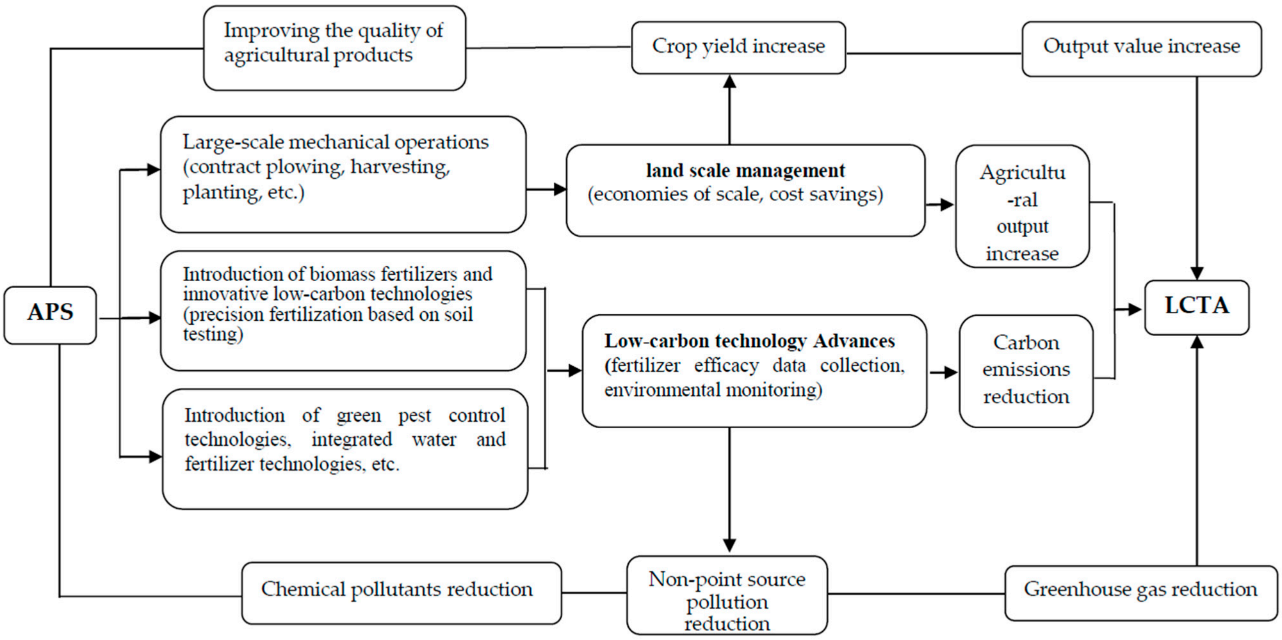

Figure 1. Theoretical framework showing the relationship between APS and LCTA.

Firstly, when considering the environmental Kuznets theory, the effect of APS on LCTA could have a non-linear relationship. During the early stages of APS development, unregulated growth in market capital might lead to the emergence of monopolistic conditions [56]. Exclusive control over the provision of productive services frequently leads to higher service prices, which then raise production costs throughout the agricultural industry. As a result, the increased expenses related to APS usage decrease farmers' earnings and their willingness to invest in these services. Consequently, high-carbon agricultural methods may continue for some time due to the influence of production goals. As the market competitiveness mechanisms in the APS sector enhance, competitive pressures lead to a decrease in service costs. Reduced input costs increase farmers' profit margins, making them more willing to outsource services at various stages of production. The LCTA has advanced as a result of this transition from high-carbon practices to labor-saving and low-carbon technologies [57]. Based on the previous theoretical foundation, we proposed Hypothesis 1 in the following manner.

Hypothesis 1. *The impact of APS on the LCTA is to be nonlinear, with the existence of certain threshold ranges.*

Furthermore, by applying the theory of division and specialization, the incorporation of APS into the agricultural production process promotes the growth of agricultural sectors [14]. Smallholder farmers, who labor on small and fragmented plots of land, experience longer operational times and faster machinery wear when applying APS to these scattered plots. As a result, service providers frequently favor large-scale operators rather than smallholders. Within this particular framework, APS organizations provide extensive mechanized services, including contract plowing, harvesting, and planting. This encourages small-scale farmers to combine their enterprises into larger ones (Figure 1), allowing them to take advantage of economies of scale, lower service costs, increase agricultural output, and improve profits [58], thus removing the necessity for individual investment in farming machinery. Furthermore, in comparison to purchases made by individual farmers, APS providers are capable of delivering agricultural film, fertilizers, and pesticides of higher quality at reduced prices due to their operational scope [41]. Therefore, based on the previous study, we put forward Hypothesis 2.

Hypothesis 2. *APS can indirectly facilitate the LCTA by promoting the large-scale operation of farmland.*

Furthermore, according to transition economics theory, technological advancement plays a vital role in attaining transformative development. In his derivation of the production function, Solow [59] showed that the marginal advantages of labor, capital, and natural resources decline over time, while knowledge and technology do not exhibit declining marginal returns. This suggests that investing in modern technology and existing knowledge does not increase marginal costs. Extending Solow's findings, subsequent research clarifies the shift from a dichotomy between economic transformation and environmental improvement to a synergistic relationship [54]. Therefore, continuous investment in low-carbon agricultural technology such as soil testing, precision fertilization, digital monitoring of fertilizer efficacy, and green pest management would help reduce chemical and diffuse agricultural pollution. By using advanced low-carbon and eco-friendly technology, the simultaneous implementation of this initiative will improve the efficiency of environmental governance and reduce carbon emissions in agriculture. Ultimately, this will lead to the low-carbon transformation of agricultural development. Based on the previous study, we propose Hypothesis 3.

Hypothesis 3. *Agricultural productive services can indirectly facilitate the LCTA through the advancement of low-carbon technologies.*

3. Model Specifications and Data

3.1. The Measurement of APS

In this study, agriculture is narrowly defined as crop farming. Up to now, there is no direct indicator for measuring the level of APS. Scholars employ a range of indirect indicators to assess APS, including funds allocated to productive services in rural fixed asset investment [60]; intermediate services of agricultural input in input-output tables [39], and expenditures on productive services related to agriculture [14]. These indicators have either been discontinued at the provincial level or have been collected inconsistently in recent years, which may lead to overestimation or underestimation of the actual situation. Consequently, we utilize the average value per acre of support service activities for crop farming, as reported by the National Bureau of Statistics, to gauge APS. Supportive services encompass professional and auxiliary production activities such as seedling breeding, agricultural machinery, irrigation, and pest and disease control for sectors like crop farming, forestry, animal husbandry, and fisheries. These offerings reflect, to some degree, the scope of services that enhance agricultural productivity and are conceptually in harmony with APS. Additionally, this dataset has been consistently available for more than two decades, given that the macro provincial level aggregates the output value of professional and supportive services for the whole of agriculture. As such, the value of supportive services for crop farming presented in this paper requires adjustment. The calculation formula is as follows:

$$\text{APS}_{it} = \frac{T\text{APS}_{it} \times (AV_{it}/TAV_{it})}{Scale_{it}} \quad (1)$$

where APS_{it} is the value of agricultural support services for region i in year t, $T\text{APS}_{it}$ is the value of support services for crop farming, forestry, animal husbandry, and fisheries, AV_{it}/TAV_{it} is the proportion of crop farming output value in the total output value of agriculture, $Scale_{it}$ is the sown area of crops.

3.2. The Measurement of Agricultural Carbon Emissions

Drawing from the environmental Kuznets theory, the transition to LCA necessitates the integration of low-carbon technologies to mitigate emissions and promote clean production, while simultaneously fostering agricultural economic growth to secure food supplies. Consequently, this study adopts carbon emission intensity as a measurable indicator of the agricultural sector's shift towards low-carbon practices. The calculation formula is as follows:

$$\mathrm{ACI}_{it} = AC_{it} / AG_{it} \quad (2)$$

In the formula, ACI_{it} represents the agricultural carbon intensity for region i in year t, AC_{it} represents the total ACEs, and AG_{it} represents the actual total agricultural output value.

Current methodologies for calculating agricultural carbon emissions (AC_{it}) primarily utilize an input-output approach to estimate the aggregate carbon emissions across the agricultural production process (Figure 2). First, inputs used in production, including pesticides, fertilizers (like phosphate and potassium), agricultural plastics, and diesel, lead directly to the emission of carbon dioxide (CO_2). Furthermore, the remnants of nitrogen-based fertilizers primarily release nitrous oxide (N_2O), a gas that negatively affects the soil's health in farmed areas. Second, the planting and management of crops, involving activities like plowing and irrigation, lead to the production of carbon dioxide (CO_2). Third, methane (CH_4) emissions occur during the growth of rice, a significant factor to be accounted for in the calculation of ACEs. As a major food crop in China, rice growth has contributed to over 22.74% of the nation's ACEs [61]. Fourth, in the output stage, handling the crop remnants that are reintegrated into the soil leads to the release of multiple pollutants, including carbon dioxide, nitrous oxide, and methane. Two primary methods exist for calculating agricultural greenhouse gas emissions: the carbon emission factor approach [62] and the actual field measurement approach [63]. Given the research data in this paper are at the macro level, it is more appropriate to adopt the carbon emission factor method. The precise calculation methodology is outlined below:

$$AC_{it} = \sum C_i = \sum T_i \times \delta_i = C_{it}^1 + C_{it}^2 + C_{it}^3 + C_{it}^4 \quad (3)$$

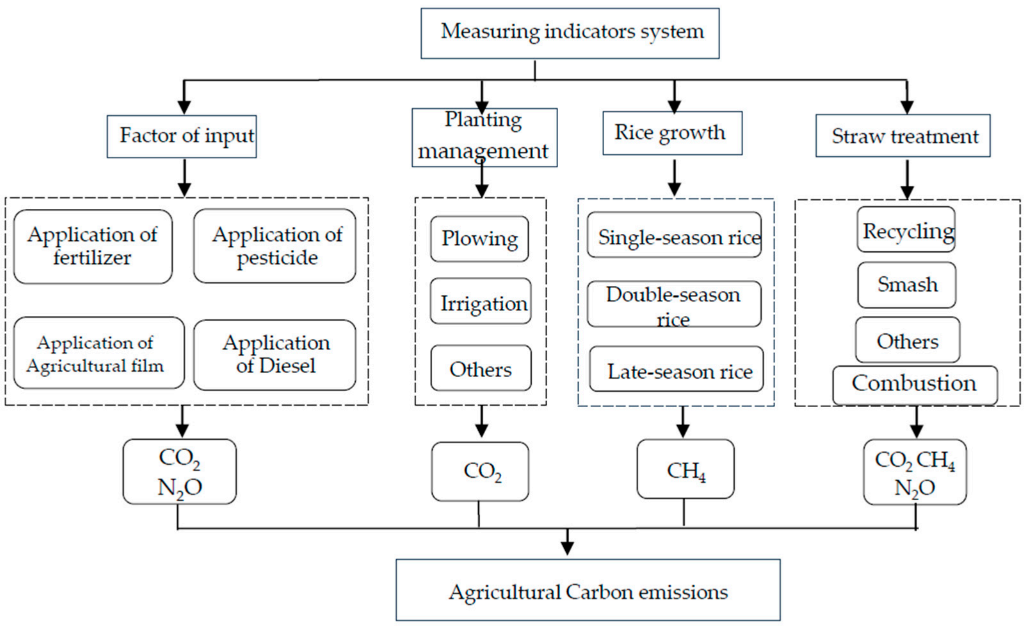

Figure 2. The calculating indicators system for agricultural carbon emission and measurement indicators. Note: All N_2O and CH_4 have been converted to carbon dioxide according to the conversion coefficient.

In Formula (3), C_i represents the ACEs; T_i and δ_i denotes the actual amount of each carbon source and the corresponding coefficient of ACEs, respectively. This paper's agricultural greenhouse gas emissions include three gases: CH_4, N_2O, and CO_2. To facilitate aggregation and maintain consistency with other carbon emission studies, this paper converts all kinds of AGHGs into standard carbon dioxide equivalents in the actual calculation. Based on the Fifth Assessment Report by the IPCC [64], the factors for converting carbon dioxide to methane and nitrous oxide stand at 28 and 265, respectively. For precise calculations of greenhouse gas emissions from various agricultural carbon sources, see Appendix A.

3.3. Variable Selection and Data Description

To examine the impacts of APS on the LCTA, this study selected one dependent variable (ACI), one independent variable (APS), seven control variables, and two mediator variables to construct a panel econometric model. Table 1 displays the chosen variables along with their descriptive statistical analysis. The specifics are as follows:

Table 1. Variable selection and descriptive statistics.

Variable	Basis	Unite	Mean	Std. Dev.	Min	Max
Agricultural carbon emission intensity (ACI)	Agricultural carbon emissions/Actual GDP (log processing)	682	2.2843	1.4413	0.2197	11.4765
Agricultural productive services (APS)	Value of agricultural support services/farmland area	682	8.4123	6.7414	0.0001	39.1855
Farmland management scale (SCALE)	Farmland area/number of agricultural households	682	0.2565	0.1625	0.0306	1.4053
Agricultural technology progress (TCH)	Regional agricultural science and technology expenditure/total agricultural expenditure	682	0.0017	0.0014	0.0001	0.0072
Farmers' education level (EDU)	Per capita years of farmer education	682	8.5651	1.2692	3.4024	12.7244
Level of economic development (GDP)	Gross regional product per capita	682	9.2149	0.5541	7.8867	10.8156
Multiple cropping index (MCC)	Crop sown area/total cultivated area	682	1.3304	0.5223	0.4856	8.2514
Agricultural fiscal expenditure (AFS)	Agricultural fiscal expenditure/farmland area	682	8.3561	1.6499	4.9223	13.3997
Natural disaster rate (DISA)	Crop affected area/total farmland area	682	0.2178	0.1596	0.0156	0.9358
Rural power infrastructure (API)	Rural electricity consumption/total regional electricity consumption	682	0.1177	0.1001	0.0065	0.7024
Agricultural machinery input (AML)	Total power of agricultural machinery/total farmland area	682	0.5886	0.3347	0.1317	2.4626

(1) The education level of farmers (EDU).

The education levels among farmers vary, leading to differences in their awareness and adoption of low-carbon technologies. More educated farmers typically have heightened environmental awareness and are likelier to engage in low-carbon agricultural practices [41]. In the model, this variable is measured by the per capita years of schooling.

(2) Agricultural economic development (GDP).

Agricultural economic development levels, as measured by GDP, may exhibit a relationship with ACI that aligns with the environmental Kuznets curve (EKC) hypothesis. At lower agricultural development stages, profit-driven farmers might intensively apply chemical inputs, along with widespread land cultivation, leading to increased agricultural carbon emissions. Research findings suggest that as technology progresses and economic expansion occurs, there is a corresponding rise in economic development. This escalation, in turn, heightens the probability that farmers will embrace technologies that are low in carbon emissions, thereby mitigating the impact of agriculture on carbon output [46,54]. In the model, this variable is controlled by using per capita GDP.

(3) The multiple cropping index of cultivated land (MCC).

MCC represents the degree of land use and is positively correlated with ACEs [29]. In our model, we measure the ratio of the planted area of crops to the total area of cultivated land.

(4) Agricultural fiscal expenditure (AFS).

AFS serves as a crucial external mechanism to foster the LCTA. Given the positive externalities of low-carbon agricultural production, agricultural fiscal expenditures can effectively motivate farmers toward low-carbon practices and enhance agricultural productivity [65]. This metric is gauged by the ratio of agricultural fiscal expenditure to crop-sown area.

(5) The extent of crop disaster (DISA).

DISA represents a stochastic event that negatively impacts low-carbon agricultural production. An increase in DISA correlates with reduced agricultural output [14], posing a detriment to low-carbon agricultural production. The severity of agricultural calamity is gauged by comparing the area impacted by the disaster to the overall area planted.

(6) Rural electricity infrastructure (API).

API may elevate energy consumption per unit of output and enhance ACEs when rural areas rely on fossil fuels for agricultural production. Given data availability, the proportion of rural electricity consumption and regional total electricity consumption is a proxy variable.

(7) Agricultural machinery input (AML).

AML can effectively replace labor and improve labor productivity with the advancement of agricultural mechanization [11], promoting agricultural economic development. However, the rise in mechanized manufacturing could lead to higher carbon emissions as it entails the extensive use of fossil fuels. Yet, AML might have a negative impact on ACI by increasing agricultural output value. Following existing literature [36], we introduce the proportion of the cumulative power of farm machinery relative to the overall area seeded with crops as a metric for evaluation.

As the theoretical analysis section suggests (Figure 1), agricultural productive services may indirectly influence the LCTA by enhancing farmland operation scale and low-carbon technology advancement. Consequently, this study identifies two mediating variables to assess their impact on the relationship between APS and the LCTA. Farmland operation scale (SCALE) is expressed specifically by the proportion of crops' sown area to the number of agricultural households. This implies that rural households with larger operational scales tend to invest in agricultural productive services for more intensive farming practices [50]. Technological progress (TCH) serves as the intrinsic driving force behind low-carbon transformational development. Given that the government might boost scientific and technological investment in agriculture to optimize low-carbon production and reduce ACEs [8], we adopt the variable of technological progress (TCH). The specific metric employed is the proportion of regional agricultural scientific expenditures to total expenditures, contingent on data availability.

This research utilizes a panel data set covering the period from 2000 through 2021 for empirical examination. It sources indicators to compute the Agricultural Carbon Intensity (ACI), such as crop yield and farmland area, from the "China Rural Statistical Yearbook". Additionally, one can find the carbon emission coefficients in Appendix A for reference. Data relevant to Agricultural Productive Services (APS) originate from the "China Tertiary Industry Statistical Yearbook". Other pertinent variables have been gathered from the "China Statistical Yearbook". Data gaps in the aforementioned yearbooks were obtained from the provincial statistical yearbook. To account for inflation, this article sets the year 2000 as the base period, adjusting the agricultural output value and regional GDP to constant prices. Additionally, a 1% bilateral trimming is applied to continuous variable indicators.

3.4. Econometric Models Linking the Effect of APS on LCTA

To verify the impact of APS on LCTA, we first employ a foundational panel econometric model, which is structured in Formula (4).

$$LnACI_{it} = \alpha_i + \beta_1 \text{APS}_{it} + \delta_j Z_{it,j} + \varepsilon_{it} \quad (4)$$

In the formula, $LnACI_{it}$ represents the logarithmic value of the ACEs intensity for the i province in the t-th year, which serves as an indicator of the LCTA. APS_{it} represents the status of APS; $Z_{it,j}$ denotes control variables, including EDU, GDP, MCC, AFS, DISA, API, AML; α_i captures individual effects; β_1 and δ_j are the coefficients for APS_{it} and control variables, respectively; ε_{it} is the stochastic error term.

To verify the nonlinear effects of varying APS levels on LACT, research on nonlinear relationships is predominantly categorized into two types. The first is the "U-shaped" hypothesis, suggesting that past a specific threshold, the effect reverses; the second type is known as a threshold–effect relationship. The limitation of the "U-shaped" hypothesis is its assertion of a definitive U-shaped or inverted U-shaped relationship, which may be arbitrary. The latter model describes the relationship as nonlinear and contingent upon key economic variables, a more reasonable approach. Consequently, in accordance with threshold model theory [66], we establish a basic static panel threshold model to serve as the benchmark for empirical analysis.

$$LnACI_{it} = \alpha_i + \beta_{11} \text{APS}_{it} \times I(\text{APS} \leq \lambda) + \beta_{12} \text{APS}_{it} \times I(\text{APS} \geq \lambda) + \delta_j Z_{it,j} + \varepsilon_{it} \quad (5)$$

$$\begin{aligned} LnACI_{it} \quad &= \alpha_i + \beta_{11} \text{APS}_{it} \times I(\text{APS} \leq \lambda_1) + \beta_{12} \text{APS}_{it} \times I(\lambda_1 \leq \text{APS} \leq \lambda_2) \\ &+ \beta_{22} \text{APS}_{it} \times I(\text{APS} \geq \lambda_2) \delta_j Z_{it,j} + \varepsilon_{it} \end{aligned} \quad (6)$$

$$\begin{aligned} LnACI_{it} \quad &= \alpha_i + \beta_{11} \text{APS}_{it} \times I(\text{APS} \leq \lambda_1) + \beta_{12} \text{APS}_{it} \times I(\lambda_1 \leq \text{APS} \leq \lambda_2) \\ &+ \beta_{22} \text{APS}_{it} \times I(\lambda_2 \leq \text{APS} \leq \lambda_3) + \beta_{31} \text{APS}_{it} \times I(\text{APS} \geq \lambda_3) \\ &+ \delta_j Z_{it,j} + \varepsilon_{it} \end{aligned} \quad (7)$$

Equations (5)–(7) correspond to the models of single-threshold panel, double-threshold panel, and triple-threshold panel, in that order. Here, $I(\cdot)$ denotes the threshold indicator function; represents the threshold value; β_{11}, β_{12}, β_{22}, β_{31} are the estimated parameters before and after the threshold for the core variable. Other variables are explained in Equation (1). Since static panel threshold models do not take into account the path dependency and persistence characteristics of induced variables, and also require the core variables to be strictly exogenous, which is difficult to fully satisfy in real economic activities [67], this study extends Equation (2) into a dynamic threshold model using the GMM estimation method, effectively addressing the issues of endogeneity.

$$\begin{aligned} LnACI_{it} \quad &= \alpha_i + \varphi_0 LnACI_{i,t-1} + \beta_{11} \text{APS}_{it} \times I(\text{APS} \leq \lambda) \\ &+ \beta_{12} \text{APS}_{it} \times I(\text{APS} \geq \lambda) + \delta_j Z_{it,j} + \varepsilon_{it} \end{aligned} \quad (8)$$

In Equation (8), $LnACI_{i,t-1}$ represents the variable of agricultural production carbon emission intensity lagged by one period.

To further analyze the logical relationships and pathways of action between APS, mediating variables, and LCTA, this paper employs Taylor's mediation effect model for stepwise regression [68]. Theoretical analysis suggests that the development of APS may advance the expansion of the scale of farmland management, generating economies of scale, and thereby affecting the value of agricultural production. Progress in agricultural technology can reduce chemical pollutants in agriculture and also decrease ACEs by enhancing low-carbon and green clean technologies, achieving LCTA. The designated mediation effect model is as follows:

$$LnACI_{it} = \alpha_i + a_1 \text{APS}_{it} + \delta_1 Z_{it} + \varepsilon_{it} \quad (9)$$

$$M_{it} = \gamma_i + b\mathrm{APS}_{it} + \delta_2 Z_{it} + \varepsilon_{it} \tag{10}$$

$$LnACI_{it} = \alpha_i + a_2\mathrm{APS}_{it} + c_1 M_{it} + \delta_3 Z_{it} + \varepsilon_{it} \tag{11}$$

M_{it} represents the mediating variable, which is denoted by SCALE and TCH, respectively. Other variables are as explained in Equation (1). A mediating effect exists when the coefficients a_1, b and c_1 are all significant.

We will use the software STATA16.0 to carry out the econometric analysis of the above models.

4. Results and Discussions

4.1. Baseline Models Results

To avoid "spurious regression", a unit root check is performed on panel data. The test results show that all variables are stationary series. Concurrently, the Hausman test value was 46.44, which passed the significance test at the 1% level, indicating the rejection of the null hypothesis for the random effects model (RE); hence, a fixed effects model was adopted. Table 2 shows the estimated results. In models (1) and (2), the coefficients for APS are significant at the 1% level, incorporating provincial and year-fixed variables in the model (2). Considering the issue of missing variables, we introduced control variables in models (3) and (4), and the coefficients for APS remained negative and significant. This indicates that APS has an inhibitory effect on *LnACI*. Additionally, to avoid endogeneity issues and improve the robustness of regression results, in models (5) and (6) we replaced APS with its first lag, APS_{t-1}, and the coefficient for APS_{t-1} is still negative and significant.

Table 2. Results of the baseline models.

Variables	lnACI	lnACI	lnACI	lnACI	lnACI	lnACI
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
APS	−0.3452 ***	−0.0237 ***	−0.0202 ***	−0.1731 **		
	(0.0292)	(0.0081)	(0.0031)	(0.0688)		
APSt−1					−0.0152 ***	−0.1643 **
					(0.0881)	(0.0067)
EDU			−0.1823 ***	−0.1332 *	−0.1801 ***	−0.1378 *
			(0.0196)	(0.0775)	(0.0197)	(0.0764)
GDP			−0.0020 ***	−0.0092	−0.0006 ***	−0.0105
			(0.0350)	(0.0096)	(0.0000)	(0.0982)
MCC			0.0764 ***	0.0570 ***	0.0713 ***	0.0523 *
			(0.0209)	(0.0336)	(0.0208)	(0.0307)
AFS			−0.0014 ***	−0.0007 ***	−0.0003 ***	−0.0001 ***
			(0.0038)	(0.0022)	(0.0002)	(0.0002)
DISA			−0.0299	−0.0846	0.4895	−0.0200
			(0.0625)	(0.0837)	(0.3318)	(0.0682)
API			0.8379 ***	−0.3170 *	−0.2635 **	−0.2732 *
			0.1841	(0.1724)	0.1290	(0.1559)
AML			−0.4453 **	0.0228	−0.1420 ***	0.0149
			(0.0506)	0.0910	(0.0518)	0.0887
Year fixed	No	Yes	No	Yes	No	Yes
Regional fixed	No	Yes	No	Yes	No	Yes
Constant	1.3038 ***	1.0698 ***	2.2715 *	1.9912 ***	2.5510 **	2.1374 ***
	(0.0213)	(0.0480)	(0.1667)	(0.5660)	(0.1643)	(0.5552)
N	682	682	682	682	682	682
R^2	0.1626	0.6705	0.5642	0.7222	0.6871	0.7121

Note: Standard errors in parentheses; * $p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$.

After including two-way fixed effects and control variables, model (4) exhibits the highest level of fit, and its regression findings are the most persuasive. There is substantial evidence indicating that APS can enhance the LCTA. This is because APS has stimulated the strategic allocation of resources, forcing small-scale growers to participate in coordinated, extensive agricultural activities. This has advanced the development of farm management by promoting the expansion and intensification of operations. Similarly, previous studies have confirmed the low-carbon performance of APS [9].

4.2. Results of Panel Threshold Models of APS on LCTA

Given the variability in APS levels, it is imperative to examine the existence of a threshold for APS. The approach presented above depends on exogenous sample selection, which may introduce estimation bias. Thus, we intend to use the panel threshold model to conduct a more in-depth analysis of this phenomenon.

Consistent with accepted techniques in the literature, we utilized the bootstrap method to determine the threshold values by conducting 300 iterations of bootstrapping. Table 3 shows that the F-values for the single and double threshold tests are statistically significant, whereas the F-value for the triple threshold test is not statistically significant. Based on our analysis, we can determine that there is a threshold effect on the level of agricultural productive services. The impact of APS on LCTA is not the same across all threshold intervals but rather varies asymmetrically. The LR test was employed to estimate the threshold values to validate their authenticity. With threshold values of 2.4396 and 15.0736, as illustrated in Figure 3, the LR statistic converges to zero. Furthermore, the LR test statistic reaches a value lower than 7.35, indicating that the threshold values estimated in our study are valid.

Table 3. Results of the threshold value test.

Threshold Estimates	Threshold Value	Fstat	Prob	Crit10	Crit5	Crit1
Single threshold test	2.4396 ***	42.05	0.0100	30.8355	33.8497	41.0753
Double threshold test	15.0736 *	29.90	0.0667	25.8527	32.0978	50.3004
Triple threshold test	4.8809	6.71	0.8767	28.2490	36.2104	46.2855

Note: * $p < 0.1$ and *** $p < 0.01$.

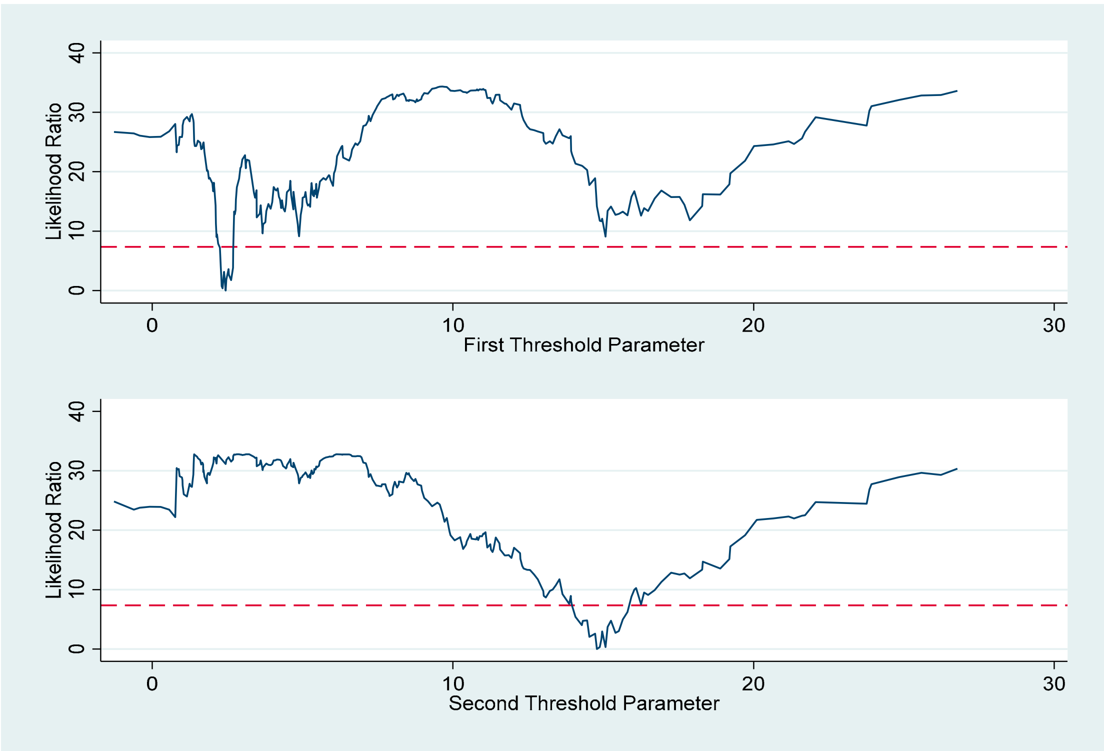

Figure 3. The LR test of the threshold value.

The results of panel threshold regression are represented by models (1) and (3), while models (2) and (4) include control variables and account for fixed effects, as shown in Table 4. At λ = 2.4396 and λ = 15.0736, both threshold effects satisfy their corresponding significance tests. When the APS is below 2.4396, the coefficient shows a statistically significant positive effect at the 1% level, indicating a clear promotion of lnACI. This suggests that during the early phases of agricultural productivity, the high costs of services discourage farmers from using APS, which leads to the continued use of high-carbon production methods that increase ACI. On the other hand, when the APS falls within the range of 2.4396 and 15.0736, the coefficient becomes negative with a significance level of 1%. This indicates that as APS improves and the costs of agricultural services decrease, farmers are increasingly adopting these cost-effective services. They integrate low-carbon technologies and knowledge into their practices, which in turn has a suppressive effect on the ACI. When the APS is above 15.0736, the effect on ACI continues to decrease. This is shown by a coefficient of −0.0142, which is slightly less significant than the −0.0205 reported in the previous range. The rising levels of APS highlight the significance of APS in promoting carbon emission reductions in agriculture, hence proving the asymmetrical nature of the threshold effect and supporting Hypothesis 1.

Table 4. Results of panel threshold models.

Variables	lnACI	lnACI	lnACI	lnACI
	(1)	(2)	(3)	(4)
Threshold estimates				
λ_1	2.0269	2.4396	2.0269	2.4396
λ_2			15.0736	15.0736
APS (<2.4396)	0.0622 ***	0.0314 ***	0.2285 ***	0.0268 ***
	(0.0134)	(−0.0068)	(0.0406)	(0.0071)
APS (2.4396 $\leq$ APS < 15.0736)	−0.04123 ***	−0.0127 ***	−0.1382 ***	−0.0205 ***
	(0.0015)	(−0.0013)	(0.0067)	(0.0019)
APS ($\geq$15.0736)			−0.0902 ***	−0.0142 ***
			(0.0041)	(0.0014)
EDU		−0.1311 ***		−0.11947 ***
		(0.0135)		(0.0133)
GDP		−0.00001 ***		−0.00001 ***
		(0.0002)		(0.0002)
MCC		0.0458 ***		0.0385 ***
		(−0.0139)		(0.0137)
AFS		0.0004 ***		0.0002 **
		(0.0001)		(0.0001)
DISA		−0.0664		−0.0668
		(0.0416)		(0.0407)
API		−0.3618 ***		−0.3201 ***
		(0.0851)		(0.0835)
AML		−0.0224		0.0167
		(0.0347)		(0.0347)
Year fixed effect	Yes	Yes	Yes	Yes
Regional fixed effect	Yes	Yes	Yes	Yes
Constant	0.9900 ***	2.4713	3.2688	2.3841
	(0.0146)	(0.1032)	(0.0496)	(0.1022)
N	682	682	682	682
R^2	0.5705	0.6634	0.4953	0.6787

Note: Standard errors in parentheses; ** $p < 0.05$, and *** $p < 0.01$.

A further examination was carried out on the distribution of provinces across different APS thresholds from 2000 to 2021, as illustrated in Figure 4. APS was classified into three levels: low, medium, and high, based on the values of λ = 2.4396 and λ = 15.0736, which represent the effectiveness of APS on ACI. The data showed a consistent annual rise in medium- and high-APS levels in most Chinese cities, accompanied by a yearly decrease in low APS levels. This suggests that APS has successfully implemented its role in assisting the decrease of ACI in most provinces. Importantly, the occurrence of medium-level APS has increased since its peak in 2010, indicating a greater overall effect of APS on ACI reduction from 2010 to 2021. This trend presents new insights for advancing China's agricultural sector towards the peak of carbon emission actions.

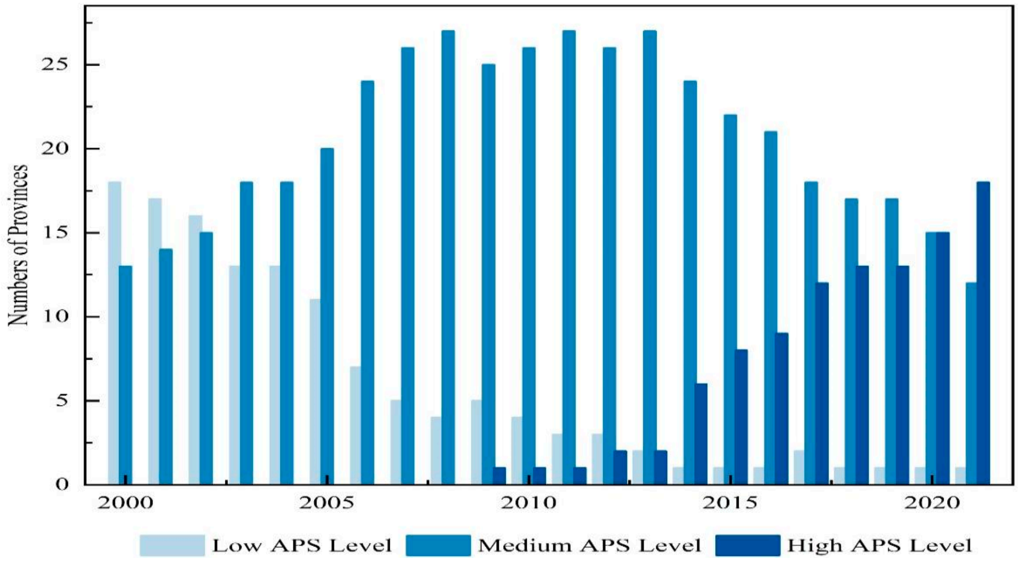

Figure 4. The number distribution of areas with different APS levels from 2000 to 2021.

Figure 5 depicts the promotion of APS in different provinces around the country in 2011 and 2021. In 2011, most provinces across the country had a moderate level of APS, except for Gansu Province, which had a high APS level. By 2021, the provinces with a high APS level were primarily located in the eastern coastline areas, central regions, and northwestern provinces of China. This includes Beijing, Shanghai, Tianjin, and China's main grain-producing areas. It is noteworthy that the central and western regions of China, except Xinjiang, continue to advance the reduction of ACE at a relatively low level of APS. Hence, to promote the LCTA more effectively, particularly in the western and northern regions, it is critical to accelerate the development of APS.

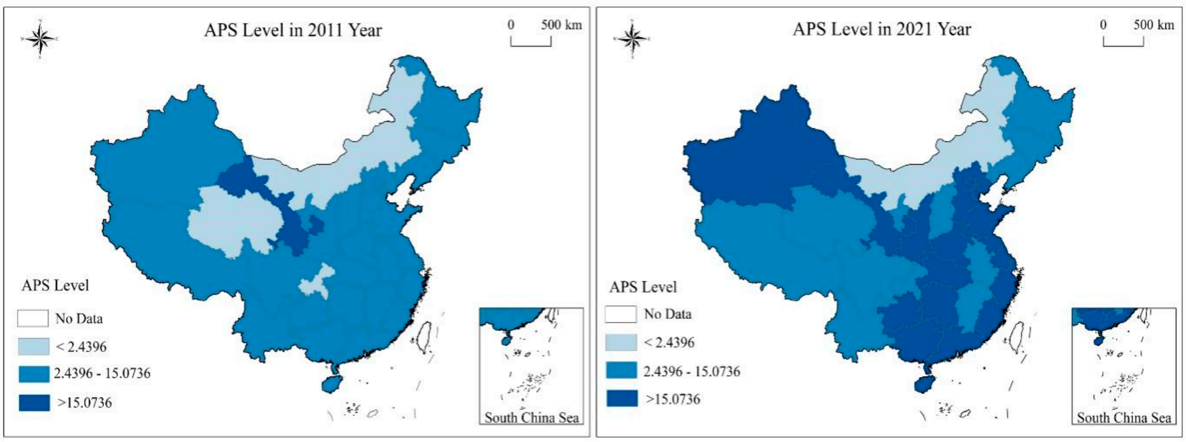

Figure 5. Regional distribution of different APS levels in 2010 and 2020.

4.3. Robustness Check

To address the shortcomings of the static threshold model, we employed a dynamic threshold model to assess the robustness of the estimations. The study used the lnACI and APS variables, as well as their lagged counterparts (L.lnACI and L.APS), to address endogeneity issues. The estimation findings from Table 5 indicate that in models (1) and (2), the inclusion of L.lnACI leads to a consistent single threshold estimate of 2.3065, while the double threshold estimate remains unchanged. Furthermore, all coefficient values successfully pass the 1% statistical test, providing additional confirmation of the asymmetric threshold impact of APS on lnACI. This effect entails that APS initially stimulates lnACI and subsequently reduces it. When analyzing model (3) with the lagged APS variable, the threshold value remains the same, and all coefficients are statistically significant. This demonstrates the rationality of the dynamic model configuration, where the APS from the previous period first has a positive impact and then a negative impact on the current period's lnACI. When the value is beyond the threshold of 2.4396, the impact on lnACI increases dramatically. However, once it goes over the threshold of 15.0736, the degree of impact weakens. This further confirms the robustness of the research findings for Hypothesis 1.

Table 5. Results of robustness check using the threshold model.

Variables	lnACI	lnACI	lnACI
	(1)	(2)	(3)
L.lnACI	0.5727 ***	0.5532 ***	
	(0.0295)	(0.0298)	
APS (<2.3065)	0.0109 ***	0.0126 ***	
	(0.0017)	(0.0070)	
APS (2.3065 ≤ APS < 15.0736)	−0.0065 ***	−0.0112 ***	
	(0.0012)	(0.0016)	
APS (≥15.0736)		−0.0069 ***	
		(0.0011)	
L.APS (<2.4396)			0.0200 ***
			(0.0072)
L.APS (2.4396 ≤ APS < 15.0736)			−0.0167 ***
			(0.0024)
L.APS (≥15.0736)			−0.0115 ***
			(0.0014)
EDU		−0.0496 ***	−0.1247 ***
		(0.0112)	(0.0138)
GDP		−0.00005 **	−0.00001 ***
		(0.0002)	(0.0003)
MCC		0.0137	0.0394 ***
		(0.0108)	(0.0140)
AFS		0.0001	0.0029 *
		(0.0001)	(0.0015)
DISA		−0.05419	−0.0178
		(0.0334)	(0.0433)
API		−0.0645	−0.2506 ***
		(0.0681)	(0.0879)
AML		0.0046	−0.0197
		(0.0283)	(0.0364)
Year fixed effect	Yes	Yes	Yes
Regional fixed effect	Yes	Yes	Yes
Constant	1.0263 ***	1.0421 ***	2.4141 ***
	(0.1080)	(0.1071)	(0.1068)
N	682	682	682
R-squared	0.7897	0.7937	0.6525

Note: Standard errors in parentheses; * $p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$.

4.4. Mediating Effect of APS on LCTA

The mediation effect model proposed by Taylor [68] was used to examine the pathways by which APS influences LACT, as measured by InACI in Table 6. The initial analysis focused on the overall impact of APS on LACT. The model (1) showed a statistically significant negative coefficient for APS (−0.1731). The reason for this result can be ascribed to the enduring impacts of APS, which successfully reduce the limitations arising from resource endowments like labor and technology for farmers. In addition, APS can cause a change in the practices of smallholders, who often depend on experiential knowledge for agricultural production. Furthermore, APS addresses efficiency loss issues arising from the dispersed operations of small farms, thus promoting the LCTA.

Table 6. Results of the mediating effect models.

Variables	lnACI	Scale	Tech	lnACI	lnACI
	(1)	(2)	(3)	(4)	(5)
APS	−0.0204 **	0.0068 ***	0.0000433 ***	−0.0187 ***	−0.0218 ***
	(−0.0688)	(0.0009)	(0.0000651)	(0.0031)	(0.0031)
Scale				0.2518 **	
				(0.1168)	
TCH					32.8864 *
					(17.8811)
EDU	−0.1332 *	0.0991 ***	0.1134 ***	0.0318	0.0530 ***
	(−0.0775)	(0.0067)	(0.0441)	(0.0234)	(0.0205)
GDP	−0.0092	−0.0001 ***	0.0007 ***	−0.0002 ***	−0.00002 ***
	(−0.0096)	(0.0015)	(0.0079)	(0.0028)	(0.00003)
MCC	0.0570 ***	−0.0763 ***	0.2777 ***	0.3814 ***	0.3530
	(−0.0336)	(0.0105)	(0.0069)	(0.0331)	(0.0323)
AFS	−0.0007 ***	−0.0019	0.0012	−0.0001 ***	−0.0014 ***
	(−0.0022)	(0.0125)	(0.0018)	(0.0003)	(0.0023)
DISA	−0.0846	−0.1563 ***	−0.0406	0.1730	0.1350
	(−0.0837)	(0.0362)	(0.0371)	(0.1114)	(0.1100)
API	−0.3170 *	−0.0772	0.2371 ***	0.8685 ***	0.7775 ***
	(−0.1724)	(0.0605)	(0.3963)	(0.1838)	(0.1878)
AML	0.0228	−0.0358 **	0.0004	−0.4308 ***	−0.4412 ***
	(0.091)	(0.0179)	(0.0002)	(0.0547)	(0.0546)
Year fixed effect	Yes	Yes	Yes		
Regional fixed effect	Yes	Yes	Yes		
Constant	1.9912 ***	−0.2205 ***	−0.0012 ***	0.3599 **	0.3431 **
	(−0.566)	(0.0548)	(0.0003)	(0.1683)	(0.1678)
N	682	682	682	682	682
Sobel Test for Mediation Effect				Z = −2.056 **	Z = 1.733 *
Percentage of Mediation Effect (%)				8.42%	6.97%

Note: Standard errors in parentheses; * $p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$.

Furthermore, the impact of APS on the mediating variables (Scale and Tech) was investigated. According to Models (2) and (3), when considering other factors, APS showed a substantial positive correlation with both family business scale (Scale) and agricultural technological advancement (Tech). The coefficients for these correlations were 0.0068 and 0.0433, respectively. This study implies that when the level of specialization increased, expanding scale and advancing Tech indirectly benefited the LCTA. Thus, the results of Hypotheses 2 and 3 are validated.

Finally, the mediating effects of the variables Scale and Tech were examined. At the 1% significance level, the results of Models (4) and (5) indicated that Scale and Tech have a significant direct effect on lnACI, with coefficient values of 0.2518 and 32.8864, respectively. In addition, when the mediating variables were Scale and Tech, APS had a direct influence on lnACI. The findings indicate that Scale and Tech have a partially mediating effect (as shown in Figure 6), which is further supported by the results of the Sobel test reported in Table 6. This means that 8.42% and 6.97% of the influence of APS on LACT is achieved indirectly by influencing Scale and Tech to promote the LCTA. APS plays a crucial role in three areas: supporting large-scale management of farms, driving advancements in low-carbon technology, and facilitating the transition to low-carbon agriculture.

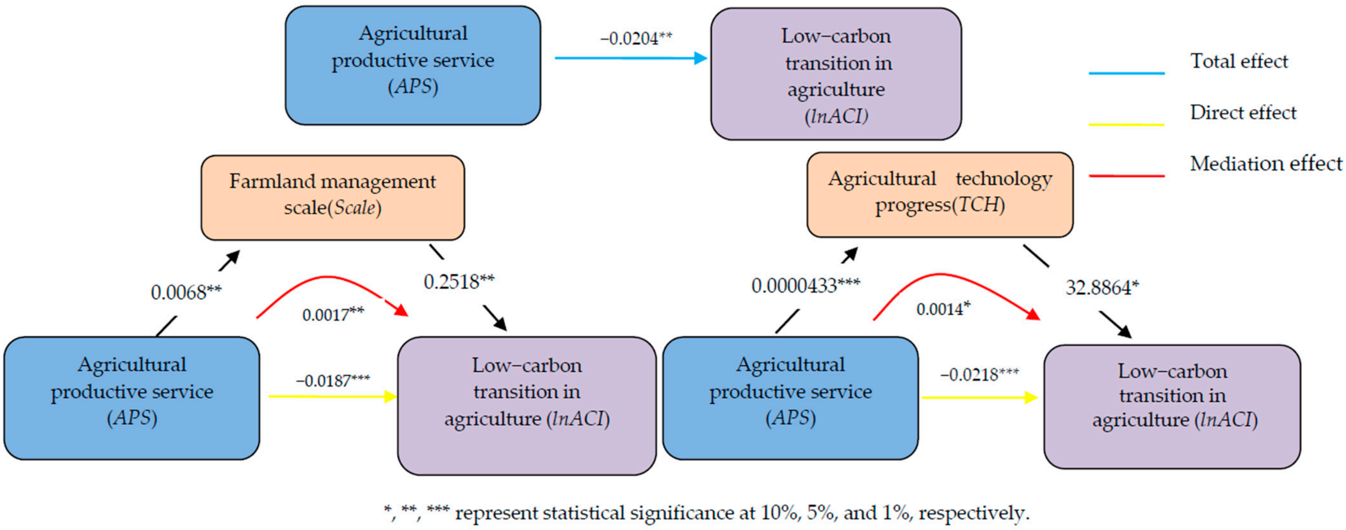

Figure 6. The path analysis of the impacts of APS on LACT.

4.5. Discussion

To accomplish China's "dual carbon" targets, this study considers the incorporation of APS into China's agricultural low-carbon production process as a logical starting point. Based on a comprehensive examination and incorporation of current literature and relevant theories, a systematic framework was developed (Figure 1). The study used national and provincial statistical data to develop a detailed econometric model. This model was used to empirically verify theoretical conclusions and research hypotheses, resulting in several valuable findings.

The impact of APS on *LnACI* demonstrated a distinct threshold value, indicating a nonlinear relationship. As the level of APS increased, their impact on the *LnACI* was initially stimulated and then suppressed, followed by a gradual suppression, with these three phases being asymmetrical. The observed static threshold values of λ_1 = 2.4396 and λ_2 = 15.0736 provide evidence of a significant threshold effect. In addition, the results of the dynamic threshold regression, which includes a lag of one period for both the dependent variable (lnACI) and the core explanatory variable (APS), indicated that while the threshold values were different from the static ones, the differentiated impacts before and after the thresholds remained consistent. This further supports the presence of a nonlinear effect.

Second, the influence of APS on *LnACI* exhibited regional heterogeneity and imbalance. As shown in Figures 4 and 5, the national APS level increased by 2021 relative to 2011. However, the Inner Mongolia Autonomous Region in northern China has maintained a consistently low APS level, which is insufficient to suppress ACI. In 2021, the provinces in China's eastern coastal areas, central regions, and a few northwestern provinces had the highest APS levels (APS $\geq$ 15.0736). These provinces are primarily located in China's main grain-producing areas. APS improves the economic benefits of the key grain-producing areas and also decreases ACEs.

Third, in terms of indirect influence and pathways, agricultural productive services can indirectly increase agricultural low-carbon transition by influencing the scale of farmland operations (Scale) and agricultural technological advancement (Tech) (as depicted in Figure 6). APS providers prefer contiguous plots of land over fragmented ones to achieve regional scale and specialized operations. Hence, the scale of farmland operations (Scale) contributed 8.42% to the promotion of LCTA. On the other hand, APS facilitated an indirect spillover into agricultural low-carbon transition by promoting low-carbon technological progress, with this factor accounting for 6.97%. Therefore, the organic incorporation of service-scale management with farmland-scale operations, together with the ongoing development of low-carbon technological progress and enhanced efficiency of agricultural input factors, would serve as the driving force behind China's future food security and LCTA [17].

5. Conclusions

The distinctive "large country, small farmers" characteristic of Chinese agriculture, as suggested by the limited research findings mentioned above, may entail various policy implications. These implications are aimed at optimizing the development of APS and promoting the LCTA, serving as valuable reference points for guidance.

Firstly, APS has the potential to comprehensively integrate modern mechanical, capital, and low-carbon technological components into agricultural production. This integration occurs through specialized, standardized, and intensive-scale services, thereby facilitating the low-carbon development of the entire agricultural production process [61]. Therefore, the Chinese government must maintain its efforts that promote the development of diverse entities in the APS market, establish a favorable institutional environment, and provide financial assistance for the market's advancement. Ensuring that the productive service requirements of farmers are adequately addressed and lowering the barriers to entry into the APS market will protect the technological dividends and scale advantages that APS provides to all farmers, particularly smallholders.

Secondly, the regional disparity in the advancement of APS presents novel challenges in the optimization of agricultural policy supply. Currently, China's main grain-producing areas (eastern and central regions) have higher APS levels, and the low-carbon transformation of these areas should be fully leveraged as a demonstration effect. Moreover, in the northern regions of China, particularly the Inner Mongolia Autonomous Region, where levels of APS are relatively low, the government could potentially increase financial assistance, establish APS-specific platforms, and foster a conducive environment for the growth of the APS sector.

Thirdly, it is imperative to consider environmental limitations, such as land fragmentation, to establish conducive external circumstances that promote service-scale operations, support land-scale operations, and ensure agricultural-scale benefits. Land-scale operations can reduce the operating costs of productive service-scale operations, such as large-scale mechanization (Liu et al., 2021) [49]. Hence, in consideration of farmers' preferences, promoting land leveling, irrigation facilities, and the development of high-standard farmland becomes crucial to decreasing external constraints such as land fragmentation on the environmental conditions necessary for scaling up productive service operations. Various regions should prioritize guiding the coordinated advancement of APS and land transfer-related policies, aiming to achieve synergistic advantages between service-scale operations and land-scale operations.

Furthermore, despite the aforementioned findings, this study has certain limitations. The study was based on an investigation of the impact of APS on the low-carbon transformation of agriculture. It primarily emphasized the analysis of provincial macro data but lacked a detailed assessment of farmers' perspectives on their desire to adopt APS or use low-carbon technologies in agricultural production at a micro-level. It is essential to conduct an empirical analysis in the future, using further micro-level data, that comprehensively depicts the integration of APS into low-carbon agricultural production, considering both macro and micro-level aspects.

Author Contributions: Methodology, X.L.; Software, X.Z., X.H. and X.L.; Formal analysis, N.G.; Resources, X.Z. and X.L.; Data curation, X.H.; Writing—original draft, N.G.; Writing—review & editing, N.G.; Supervision, X.L.; Project administration, X.Z.; Funding acquisition, N.G. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by [The national social science foundation of China program] grant number [23BJY178] and [Shandong Province Social Science Planning General Project] grant number [23CJJJ34].

Institutional Review Board Statement: Not applicable.

Data Availability Statement: The data presented in this study are available on request from the corresponding author. The data are not publicly available as "the rest of the team also needs to write papers with this data.

Conflicts of Interest: The author Xiaoqing Zheng was employed by the company Inspur Smart City 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.

Appendix A

The study calculated the AGHGs from four aspects: material inputs (chemical fertilizers, pesticides, agricultural films, and diesel), crop cultivation management, rice planting, and crop straw burning. The carbon emission coefficients are provided in Table A1.

The first is the carbon emissions from material inputs (C_{it}^1), The calculation Formula (A1):

$$C_{it}^1 = \sum_{c=1}^{3} A_{it}^c \times \delta_{it}^{1c} + \sum_{c=1}^{3} B_{it}^c \times \delta_{it}^{2c} + F_{it}^c \times \delta_{it}^3 \times \alpha_1 \quad \text{(A1)}$$

In this context, A_{it}^c represents the pure quantities of phosphorus fertilizer, potassium fertilizer, and compound fertilizer used in region i during year t, and δ_{it}^{1c} corresponds to the respective carbon emission coefficients for region i; B_{it}^c represents the usage amounts of pesticides, agricultural films, and diesel in region i during year t, and δ_{it}^{2c} corresponds to their respective carbon emission coefficients; since nitrogen fertilizers produce N_2O, a conversion factor is necessary to convert this into carbon dioxide equivalents, where F_{it}^c represents the pure quantity of nitrogen fertilizer used in land utilization, δ_{it}^3 is the carbon emission coefficient for nitrogen fertilizer, and α_1 is the conversion factor (GWP100 = 265) [64].

The second aspect is the carbon emissions produced during the plowing and irrigation processes in crop cultivation management (C_{it}^2), with the calculation formula being:

$$C_{it}^2 = D_{it}^c \times \delta_{it}^4 + E_{it}^c \times \delta_{it}^5 \quad \text{(A2)}$$

In Equation (A2), D_{it}^c and E_{it}^c represent the carbon emissions from plowing and irrigation processes respectively in region i during year t, denoted by the grain sowing area and the irrigated arable land area, respectively; δ_{it}^4 and δ_{it}^5 are the corresponding carbon emission coefficients.

The third is the methane gas (CH_4) emissions during the growth process of rice (C_{it}^3). Rice is categorized into early, medium, and late varieties. Based on the "Provincial Greenhouse Gas Emissions Inventory (2011)", the calculation of CH_4 emissions is as follows:

$$C_{it}^3 = CH_4^{rice} \times \alpha_2 \quad \text{(A3)}$$

$$CH_4^{rice} = \sum_{c=1}^{3} G_{it}^c \times \delta_{it}^{6c} \quad \text{(A4)}$$

Here in, G_{it}^c represents the respective planting areas for early, medium, and late rice in region i during year t, δ_{it}^{6c} is the corresponding ACEs coefficient (see Table A2); α_2 is the CH_4 conversion factor (GWP100 = 28) [64].

The fourth aspect involves the burning of crop residues (C_{it}^4). We have calculated the emissions of CO_2, CH_4, and N_2O resulting from the burning of residues from four major crops in China: wheat, corn, rice, and legumes. For ease of expression, the following indicators are annual statistical measures for each region. The specific calculations are as follows:

$$C_{it}^4 = C_{it}^{straw} + N_{it}^{straw} \times \alpha_1 + CH_{4it}^{straw} \times \alpha_2 \quad \text{(A5)}$$

$$\begin{aligned} C_{it}^{straw} &= \sum_{c=1}^{4} H_{it}^c \times I_{it}^c \times J_{it}^c \times K_{it}^c \times L_{it}^c \times \delta_{it}^{7c} \\ N_{it}^{straw} &= \sum_{c=1}^{4} H_{it}^c \times I_{it}^c \times J_{it}^c \times K_{it}^c \times L_{it}^c \times \delta_{it}^{8c} \\ CH_{4it}^{straw} &= \sum_{c=1}^{4} H_{it}^c \times I_{it}^c \times J_{it}^c \times K_{it}^c \times L_{it}^c \times \delta_{it}^{9c} \end{aligned} \quad \text{(A6)}$$

C_{it}^{straw}, N_{it}^{straw}, and CH_{4it}^{straw}, correspond to the emissions of CO_2, N_2O, and CH_4 from straw burning, respectively; H_{it}^{c} is the yield of four different crops in region i during year t; I_{it}^{c}, J_{it}^{c}, K_{it}^{c}, and L_{it}^{c} represent the grain–straw ratio, the dry matter proportion of straw, the combustion efficiency, and the combustion ratio for different crops, respectively. The straw burning algorithm is in reference to Li [69], and δ_{it}^{7c}, δ_{it}^{8c}, δ_{it}^{9c} represent the combustion coefficients for different crops. The statistics for each indicator can be found in Table A2.

Table A1. Description of calculation parameter.

Agricultural Activity	Carbon Source	Parameter	References
Factor of input	Phosphatic fertilizer (δ_{it}^{11})	1.63 kg (CO_2)/kg	[70]
	Potash fertilizer (δ_{it}^{12})	0.65 kg (CO_2)/kg	[70]
	Compound fertilizer (δ_{it}^{13})	1.77 kg (CO_2)/kg	[70]
	Pesticide (δ_{it}^{21})	4.9341 kg (C)/kg	[70]
	Agricultural film (δ_{it}^{22})	5.18 kg (C)/kg	[70]
	Diesel oil (δ_{it}^{23})	0.5927 kg (C)/kg	[64]
	Nitrogenous fertilizer (δ_{it}^{3})	0.0125 kg (N_2O)/kg	[64]
Planting management	Plowing (δ_{it}^{4})	312.6 kg (C)/km^2	[71]
	Irrigation (δ_{it}^{5})	266.48 kg (C)/hm^2	[62]
Rice growth	Single-season rice (δ_{it}^{61})	Table A2	[72]
	Double-season rice (δ_{it}^{62})	Table A2	[72]
	Late-season rice (δ_{it}^{63})	Table A2	[72]
Straw treatment	${\delta_{it}}^{7c}$, ${\delta_{it}}^{8c}$, ${\delta_{it}}^{9c}$	Table A3	[69]

Note: The IPCC refers to the Intergovernmental Panel on Climate Change of the United Nations, specifically from the "2014 IPCC Guidelines for National Greenhouse Gas Inventories", https://www.ipcc.ch/ (accessed on 20 December 2023); CLCD stands for the China Life Cycle Database. IREEA is the Institute of Agricultural Resources and Environmental Economics at Nanjing Agricultural University.

Table A2. Rice growth coefficient g (CH_4)/m^2.

Province (City, Autonomous Region)	Single-Season Rice	Double-Season Rice	Late-Season Rice
Beijing	0	13.23	0
Tianjin	0	11.34	0
Hebei	0	15.33	0
Shanxi	0	6.22	0
Inner Mongolia	0	8.93	0
Liaoning	0	9.24	0
Jilin	0	5.57	0
Heilongjiang	0	8.31	0
Shanghai	12.41	53.87	27.50
Jiangsu	16.07	53.55	27.60
Zhejiang	14.37	57.96	34.50
Anhui	16.75	51.24	27.60
Fujian	7.74	43.47	52.60
Jiangxi	15.47	65.42	45.80
Shandong	0	21.00	0
Henan	0	17.85	0
Hubei	17.51	58.17	39.00
Hunan	14.71	56.28	34.10
Guangdong	15.05	57.02	51.60
Guangxi	12.41	47.78	49.10
Hainan	13.43	52.29	49.4
Sichuan	6.55	25.73	18.50
Chongqing	6.55	25.73	18.50
Guizhou	5.10	22.05	21.00
Yunnan	2.38	7.25	7.60
Tibet	0	6.83	0
Shaanxi	0	12.51	0
Gansu	0	6.83	0
Qinghai	0	0	0
Ningxia	0	7.35	0
Xinjiang	0	10.5	0

Table A3. Crop straw burning.

Straw Type	CO_2 Coefficient (g/kg)	N_2O Coefficient (g/kg)	CH_4 Coefficient (g/kg)
Wheat	586.39	0.05	2.22
Maize	620.72	0.12	2.95
Rice	656.27	0.11	2.19
Beans	543.11	0.09	2.89

References

1. Ghorbani, M.; Motallebi, M. The study on shadow price of greenhouse gases emission in Iran: Case of dairy farms. *Res. J. Environ. Sci.* **2009**, *3*, 466–475. [CrossRef]
2. Hong, C.; Burney, J.A.; Pongratz, J.; Nabel, J.E.; Mueller, N.D.; Jackson, R.B.; Davis, S.J. Global and regional drivers of land-use emissions in 1961–2017. *Nature* **2021**, *589*, 554–561. [CrossRef] [PubMed]
3. Borghesi, S.; Cainelli, G.; Mazzanti, M. Linking emission trading to environmental innovation: Evidence from the Italian manufacturing industry. *Res. Policy* **2015**, *44*, 669–683. [CrossRef]
4. Kamat, A.S.; Khosla, R.; Narayanamurti, V. Illuminating homes with LEDs in India: Rapid market creation towards low-carbon technology transition in a developing country. *Energy Res. Soc. Sci.* **2020**, *66*, 101488. [CrossRef]
5. Clapp, J.; Newell, P.; Brent, Z.W. The global political economy of climate change, agriculture and food systems. *J. Peasant Stud.* **2018**, *45*, 80–88. [CrossRef]
6. Vermont, B.; De Cara, S. How costly is mitigation of non-CO_2 greenhouse gas emissions from agriculture?: A meta-analysis. *Ecol. Econ.* **2010**, *69*, 1373–1386. [CrossRef]
7. FAO. Agriculture and Forestry Greenhouse Gas Emissions Database. Available online: https://www.fao.org/statistics/en/ (accessed on 20 December 2023).
8. He, K.; Li, F.; Wang, H.; Ming, R.; Zhang, J. A low-carbon future for China's tech industry. *Science* **2022**, *377*, 1498–1499. [CrossRef] [PubMed]
9. He, P.; Zhang, J.; Li, W. The role of agricultural green production technologies in improving low-carbon efficiency in China: Necessary but not effective. *J. Environ. Manag.* **2021**, *293*, 112837. [CrossRef] [PubMed]
10. Huang, J.; Huang, Z.; Jia, X.; Hu, R.; Xiang, C. Long-term reduction of nitrogen fertilizer use through knowledge training in rice production in China. *Agric. Syst.* **2015**, *135*, 105–111. [CrossRef]
11. Lu, H.; Duan, N.; Chen, Q. Impact of agricultural production outsourcing services on carbon emissions in China. *Environ. Sci. Pollut. Res.* **2023**, *30*, 35985–35995. [CrossRef]
12. Schultz, T.W. *Transforming Traditional Agriculture*; Yale University Press: New Haven, CT, USA, 1964.
13. Arriagada, R.A.; Sills, E.O.; Pattanayak, S.K.; Cubbage, F.W.; González, E. Modeling fertilizer externalities around Palo Verde National Park, Costa Rica. *Agric. Econ.* **2010**, *41*, 567–575. [CrossRef]
14. Qian, L.; Lu, H.; Gao, Q.; Lu, H. Household-owned farm machinery vs. outsourced machinery services: The impact of agricultural mechanization on the land leasing behavior of relatively large-scale farmers in China. *Land Use Policy* **2022**, *115*, 106008. [CrossRef]
15. Qing, C.; Zhou, W.; Song, J.; Deng, X.; Xu, D. Impact of outsourced machinery services on farmers' green production behavior: Evidence from Chinese rice farmers. *J. Environ. Manag.* **2023**, *327*, 116843. [CrossRef] [PubMed]
16. Wang, H.; Wang, S.; Yu, Q.; Zhang, Y.; Wang, R.; Li, J.; Wang, X. No tillage increases soil organic carbon storage and decreases carbon dioxide emission in the crop residue-returned farming system. *J. Environ. Manag.* **2020**, *261*, 110261. [CrossRef] [PubMed]
17. Wang, R.; Zhang, Y.; Zou, C. How does agricultural specialization affect carbon emissions in China? *J. Clean. Prod.* **2022**, *370*, 133463. [CrossRef]
18. 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]
19. Massey, R.; Kientzy, D. Agriculture and Greenhouse Gas Emissions. Available online: https://extension.missouri.edu/publications/g310 (accessed on 20 December 2023).
20. Xiong, C.; Chen, S.; Xu, L. Driving factors analysis of agricultural carbon emissions based on extended STIRPAT model of Jiangsu Province, China. *Growth Chang.* **2020**, *51*, 1401–1416. [CrossRef]
21. Cole, C.; Duxbury, J.; Freney, J.; Heinemeyer, O.; Minami, K.; Mosier, A.; Paustian, K.; Rosenberg, N.; Sampson, N.; Sauerbeck, D. Global estimates of potential mitigation of greenhouse gas emissions by agriculture. *Nutr. Cycl. Agroecosyst.* **1997**, *49*, 221–228. [CrossRef]
22. Van Ha, N.; Kant, S.; Maclaren, V. Shadow prices of environmental outputs and production efficiency of household-level paper recycling units in Vietnam. *Ecol. Econ.* **2008**, *65*, 98–110. [CrossRef]
23. Wei, C.; Ni, J.; Du, L. Regional allocation of carbon dioxide abatement in China. *China Econ. Rev.* **2012**, *23*, 552–565. [CrossRef]
24. Yang, Y.; Wang, H.; Löschel, A.; Zhou, P. Patterns and determinants of carbon emission flows along the Belt and Road from 2005 to 2030. *Ecol. Econ.* **2022**, *192*, 107260. [CrossRef]
25. Ren, C.; Liu, S.; Van Grinsven, H.; Reis, S.; Jin, S.; Liu, H.; Gu, B. The impact of farm size on agricultural sustainability. *J. Clean. Prod.* **2019**, *220*, 357–367. [CrossRef]

26. Tong, X.; Brandt, M.; Yue, Y.; Ciais, P.; Rudbeck Jepsen, M.; Penuelas, J.; Wigneron, J.-P.; Xiao, X.; Song, X.-P.; Horion, S. Forest management in southern China generates short term extensive carbon sequestration. *Nat. Commun.* **2020**, *11*, 129. [CrossRef] [PubMed]
27. 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]
28. Searchinger, T.D.; Wirsenius, S.; Beringer, T.; Dumas, P. Assessing the efficiency of changes in land use for mitigating climate change. *Nature* **2018**, *564*, 249–253. [CrossRef] [PubMed]
29. Tao, Y.; Duan, M.; Deng, Z. Using an extended theory of planned behaviour to explain willingness towards voluntary carbon offsetting among Chinese consumers. *Ecol. Econ.* **2021**, *185*, 107068. [CrossRef]
30. Piwowar, A. Agricultural biogas—An important element in the circular and low-carbon development in Poland. *Energies* **2020**, *13*, 1733. [CrossRef]
31. Ali, R.; Ishaq, R.; Bakhsh, K.; Yasin, M.A. Do agriculture technologies influence carbon emissions in Pakistan? Evidence based on ARDL technique. *Environ. Sci. Pollut. Res.* **2022**, *29*, 43361–43370. [CrossRef]
32. Aguilera, E.; Reyes-Palomo, C.; Díaz-Gaona, C.; Sanz-Cobena, A.; Smith, P.; García-Laureano, R.; Rodríguez-Estévez, V. Greenhouse gas emissions from Mediterranean agriculture: Evidence of unbalanced research efforts and knowledge gaps. *Glob. Environ. Chang.* **2021**, *69*, 102319. [CrossRef]
33. Dumortier, J.; Elobeid, A. Effects of a carbon tax in the United States on agricultural markets and carbon emissions from land-use change. *Land Use Policy* **2021**, *103*, 105320. [CrossRef]
34. Abdul-Salam, Y.; Hawes, C.; Roberts, D.; Young, M. The economics of alternative crop production systems in the context of farmer participation in carbon trading markets. *Agroecol. Sustain. Food Syst.* **2019**, *43*, 67–91. [CrossRef]
35. Hu, S.; Li, D.; Wang, X. Study on the influence of carbon trading pilot policy on energy efficiency in power industry. *Int. J. Clim. Chang. Strateg. Manag.* **2023**, *15*, 159–175. [CrossRef]
36. Deng, X.; Xu, D.; Zeng, M.; Qi, Y. Does outsourcing affect agricultural productivity of farmer households? Evidence from China. *China Agric. Econ. Rev.* **2020**, *12*, 673–688. [CrossRef]
37. Shi, R.; Shen, Y.; Du, R.; Yao, L.; Zhao, M. The impact of agricultural productive service on agricultural carbon efficiency—From urbanization development heterogeneity. *Sci. Total Environ.* **2024**, *906*, 167604. [CrossRef] [PubMed]
38. Hao, A. A study of agricultural modernization and development of agricultural producer services industry—Based on provincial panel data. *Financ. Trade Econ.* **2011**, *7*, 97–102.
39. Elahi, E.; Abid, M.; Zhang, L.; Ul Haq, S.; Sahito, J.G.M. Agricultural advisory and financial services; farm level access, outreach and impact in a mixed cropping district of Punjab, Pakistan. *Land Use Policy* **2018**, *71*, 249–260. [CrossRef]
40. De Roest, K.; Ferrari, P.; Knickel, K. Specialisation and economies of scale or diversification and economies of scope? Assessing different agricultural development pathways. *J. Rural Stud.* **2018**, *59*, 222–231. [CrossRef]
41. Li, M.; Li, H.; Fu, Q.; Liu, D.; Yu, L.; Li, T. Approach for optimizing the water-land-food-energy nexus in agroforestry systems under climate change. *Agric. Syst.* **2021**, *192*, 103201. [CrossRef]
42. Sasaki, K.; Hotes, S.; Ichinose, T.; Doko, T.; Wolters, V. Hotspots of agricultural ecosystem services and farmland biodiversity overlap with areas at risk of land abandonment in Japan. *Land* **2021**, *10*, 1031. [CrossRef]
43. Cai, J.; Hu, R.; Hong, Y. Impact of farmer field schools on agricultural technology extension—Evidence from greenhouse vegetable farms in China. *Appl. Econ.* **2022**, *54*, 2727–2736. [CrossRef]
44. Sun, D.; Rickaille, M.; Xu, Z. Determinants and impacts of outsourcing pest and disease management: Evidence from China's rice production. *China Agric. Econ. Rev.* **2018**, *10*, 443–461. [CrossRef]
45. Yitayew, A.; Abdulai, A.; Yigezu, Y.A.; Deneke, T.T.; Kassie, G.T. Impact of agricultural extension services on the adoption of improved wheat variety in Ethiopia: A cluster randomized controlled trial. *World Dev.* **2021**, *146*, 105605. [CrossRef]
46. Baiyegunhi, L.; Majokweni, Z.; Ferrer, S. Impact of outsourced agricultural extension program on smallholder farmers' net farm income in Msinga, KwaZulu-Natal, South Africa. *Technol. Soc.* **2019**, *57*, 1–7. [CrossRef]
47. Rosenzweig, C.; Mbow, C.; Barioni, L.G.; Benton, T.G.; Herrero, M.; Krishnapillai, M.; Liwenga, E.T.; Pradhan, P.; Rivera-Ferre, M.G.; Sapkota, T. Climate change responses benefit from a global food system approach. *Nat. Food* **2020**, *1*, 94–97. [CrossRef] [PubMed]
48. Liu, M.; Yang, X.; Wen, J.; Wang, H.; Feng, Y.; Lu, J.; Chen, H.; Wu, J.; Wang, J. Drivers of China's carbon dioxide emissions: Based on the combination model of structural decomposition analysis and input-output subsystem method. *Environ. Impact Assess. Rev.* **2023**, *100*, 107043. [CrossRef]
49. Liu, B.; Wang, N.; Yu, M.; Zhu, X. Implicit carbon in manufacturing service factor inputs and exports: A study based on global value chain environmental cost perspective. *J. Renmin Univ. China* **2021**, *35*, 81–94. [CrossRef]
50. Huang, Y.; Xie, J. Service input and carbon emission intensity in manufacturing industry: An empirical analysis based on WIOD transnational panel. *Financ. Trade Econ.* **2019**, *40*, 100–115.
51. Youno, A.A. Increasing returns and economic progress. *Econ. J.* **1928**, *38*, 527–542.
52. Rosen, S. Specialization and human capital. *J. Labor Econ.* **1983**, *1*, 43–49. [CrossRef]
53. Becker, G.S.; Murphy, K.M. The division of labor, coordination costs, and knowledge. *Q. J. Econ.* **1992**, *107*, 1137–1160. [CrossRef]
54. Grossman, G.M.; Krueger, A.B. Economic growth and the environment. *Q. J. Econ.* **1995**, *110*, 353–377. [CrossRef]

55. Zhang, B.; Wang, B.; Wang, Z. Role of renewable energy and non-renewable energy consumption on EKC: Evidence from Pakistan. *J. Clean. Prod.* **2017**, *156*, 855–864.
56. Lyne, M.C.; Jonas, N.; Ortmann, G.F. A quantitative assessment of an outsourced agricultural extension service in the Umzimkhulu District of KwaZulu-Natal, South Africa. *J. Agric. Educ. Ext.* **2018**, *24*, 51–64. [CrossRef]
57. Huo, W.; Qi, J.; Yang, T.; Liu, J.; Liu, M.; Zhou, Z. Effects of China's pilot low-carbon city policy on carbon emission reduction: A quasi-natural experiment based on satellite data. *Technol. Forecast. Soc. Chang.* **2022**, *175*, 121422. [CrossRef]
58. Qiu, T.; Shi, X.; He, Q.; Luo, B. The paradox of developing agricultural mechanization services in China: Supporting or kicking out smallholder farmers? *China Econ. Rev.* **2021**, *69*, 101680. [CrossRef]
59. Solow, R.M. Technical change and the aggregate production function. *Rev. Econ. Stat.* **1957**, *39*, 312–320. [CrossRef]
60. Chen, K.; Liu, Y. A comparative analysis on the development status of producer services of agricultural between China and 7 foreign countries: Empirical analysis based on input-output tables. *Econ. Probl.* **2014**, *5*, 92–97.
61. Cui, Y.; Khan, S.U.; Deng, Y.; Zhao, M. Spatiotemporal heterogeneity, convergence and its impact factors: Perspective of carbon emission intensity and carbon emission per capita considering carbon sink effect. *Environ. Impact Assess. Rev.* **2022**, *92*, 106699. [CrossRef]
62. Tian, Y.; Yin, M. Re-evaluation of China's agricultural carbon emissions: Basic status, dynamic evolution and spatial spillover effects. *Chin. Rural Econ.* **2022**, *3*, 104–127.
63. Kiessé, T.S.; Corson, M.S.; Wilfart, A. Analysis of milk production and greenhouse gas emissions as a function of extreme variations in forage production among French dairy farms. *J. Environ. Manag.* **2022**, *307*, 114537. [CrossRef]
64. Change, I.C. Mitigation of climate change. In *Contribution of Working Group III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*; UNFCCC: Bonn, Germany, 2014; Volume 1454, p. 147.
65. Liu, T.; Xu, H. Post-assessment in policy-based strategic environmental assessment: Taking China's agricultural support and protection subsidy policy as an example. *Environ. Impact Assess. Rev.* **2023**, *100*, 107047. [CrossRef]
66. Hansen, B.E. Threshold effects in non-dynamic panels: Estimation, testing, and inference. *J. Econom.* **1999**, *93*, 345–368. [CrossRef]
67. Seo, M.H.; Shin, Y. Dynamic panels with threshold effect and endogeneity. *J. Econom.* **2016**, *195*, 169–186. [CrossRef]
68. Taylor, A.B.; MacKinnon, D.P.; Tein, J.-Y. Tests of the three-path mediated effect. *Organ. Res. Methods* **2008**, *11*, 241–269. [CrossRef]
69. Li, J.; Bo, Y.; Xie, S.D. Estimating emissions from crop residue open burning in China based on statistics and MODIS fire products. *J. Environ. Sci.* **2016**, *44*, 158–170. [CrossRef]
70. IKE Environmental Technology Co., Ltd. Chinese Life Cycle Database (CLCD). Available online: https://www.ike-global.com/#/products-2/chinese-lca-database-clcd (accessed on 20 December 2023).
71. Nanjing Agricultural University. International Research and Education Exchange Affairs. Available online: https://ireea.njau.edu.cn/index.htm (accessed on 20 December 2023).
72. Eggleston, S.; Buendia, L. *2006 IPCC Guidelines for National Greenhouse Gas Inventories: Intergovernmental Panel on Climate Change*; Institute for Global Environmental Strategies: Arlington, VA, USA, 2006.