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How Does Artificial Intelligence Industry Agglomeration Affect Agricultural Pollution–Carbon Reduction Synergy in China? Evidence from a Marginal Cost Perspective

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Abstract

Examining how artificial intelligence industry agglomeration (AIIA) affects carbon and pollution reduction is crucial for China's agricultural sustainability. Existing research mainly examines the effect of artificial intelligence (AI) on the reduction of single pollutants while overlooking how industry agglomeration influences the marginal cost of coordinated abatement, a key issue for the agricultural resource–environment–economy system. Using panel data for 30 Chinese provinces from 2016 to 2024, this study constructs a marginal cost-based indicator of agricultural pollution–carbon reduction synergy (APCRS) and examines the effect of AIIA. The full-sample results reveal that AIIA has a U-shaped relationship with APCRS. Technological progress partially mediates this relationship. Agricultural socialized services and rural industrial integration buffer the initial negative association, whereas agricultural labor productivity strengthens the curvature of the estimated nonlinear pattern. The effect of AIIA also varies with external conditions and is more pronounced in regions with higher levels of marketization and industrialization while remaining significantly U-shaped across grain strategic zones. This dynamic process is more likely to emerge when public innovation investment and rural household income exceed critical thresholds. These findings provide new evidence for understanding how AI-driven agglomeration can support green agricultural transformation.

Keywords: artificial intelligence industry agglomeration; agricultural pollution–carbon reduction synergy; agricultural green transformation; marginal cost; technological progress; China

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1. Introduction

Against the backdrop of the global push toward net-zero emissions and the parallel transition to greener agriculture, reducing agricultural pollution and carbon emissions has become a major concern for agricultural sectors worldwide. Over the past few years, China has achieved declines in both the total volume and intensity of agricultural carbon emissions. Although agricultural ecological conditions have improved markedly, the performance of low-carbon agricultural development still needs to be further enhanced [1]. Agriculture is highly sensitive to climate change, while climate change and extreme environmental disasters are fundamentally linked to pollution. Emissions ranging from carbon

dioxide to chemical pollutants and other contaminants, including nitrogen in agricultural runoff, can all intensify climate change. There is therefore an urgent need to promote the coordinated reduction of pollution and carbon emissions [2]. The 14th Five-Year Plan of China identifies the synergy between pollution reduction and carbon mitigation as a key pathway for promoting green development and high-quality growth. In this sense, coordinated governance of pollution and carbon emissions has become an inevitable choice for China's comprehensive green transition. As the Chinese government continues to advance the Digital China strategy, AI has thus been assigned a major role in driving the green transformation of the economy. By improving the level of green innovation and making use of advanced technologies such as machine learning models, the application of AI promotes the green transformation of firms and cities and strengthens environmental practices [3,4]. Compared with pollution from firms and urban areas, pollution in the agricultural sector is more dispersed and long-term in nature. Some scholars have theoretically analyzed the logic, operating mechanisms, and upgrading pathways through which AI can empower the green transformation of agriculture [5]. They have also pointed out existing constraints, such as the loss of effective labor and the high threshold for the use of AI-related products [6]. Nevertheless, few studies have empirically examined its impact on agricultural pollution–carbon reduction synergy (APCRS).

To advance this line of research, it is necessary to quantify APCRS. Existing studies on the synergy between pollution reduction and carbon mitigation have mainly focused on pollutant emissions [7–9], rather than adopting a comprehensive approach that integrates economic, social, and environmental factors. At the same time, to quantify the synergistic effects of agricultural pollution and carbon reduction, various methods have been adopted, including coupling coordination degree models, comprehensive indicator systems, and cross-elasticity of synergistic control [10,11]. However, these evaluation approaches primarily examine the synergistic effect from the perspective of final emissions. Emission-based indicators can show whether agricultural pollution and carbon emissions decrease, and efficiency-based indicators can evaluate overall green performance, but they cannot reveal the cost trade-off or cost-saving relationship between pollution reduction and carbon mitigation. If there is a higher APCRS value in some areas, it indicates that agricultural pollution reduction and carbon reduction are accompanied by lower joint marginal costs. Conversely, a low APCRS value implies weaker synergy or a stronger trade-off between the two environmental objectives. This indicates that the evaluation of pollution–carbon reduction synergy should not be limited to environmental outcomes but should also consider the economic costs associated with achieving these outcomes. To uphold the principle of equity, the United Nations Framework Convention on Climate Change also emphasizes that international policies and measures adopted to address climate change should take their impacts on economic development into account. This highlights the need for a measurement framework that incorporates both costs and energy-saving as well as emission-reduction performance. Therefore, the marginal cost perspective is crucial for balancing economic growth with the green transformation of agriculture.

Moreover, the impact of AI on the ecological environment remains inconclusive in existing literature. On the one hand, AI platforms allow farmers to access technical guidance and operational information, thereby reducing their learning costs. Some studies have shown that AI development affects green total factor productivity differently across regions [12], and the carbon reduction effect of AI becomes evident only after the technology reaches a certain threshold [13]. At the industrial level, by linking the internet of things with automated platforms, AI can improve production efficiency in manufacturing, enhance energy-use efficiency, and facilitate the transition toward intelligent and green industrial development [14]. On the other hand, investment in AI does not necessarily reduce carbon

emissions, and the growing diffusion of AI may also introduce environmental risks [15]. Accordingly, innovative technology is often constrained by limited technical expertise, inadequate infrastructure, and related barriers [16]. Overall, the existing literature has mainly focused on the impact of AI technology and its diffusion on the green environment, but has yet to answer the following question: how does artificial intelligence industry agglomeration (AIIA), as a techno-economic phenomenon characterized by technological spillovers and resource reorganization, affect agricultural pollution and carbon reduction synergy?

To address this gap, this study aims to examine whether and how AIIA affects APCRS in China. The specific hypotheses are developed in Section 2, focusing on the nonlinear effect of AIIA, the mediating role of technological progress, and the moderating roles of agricultural socialized services, agricultural labor productivity, and rural industrial integration. The main contributions of this study are as follows: (1) this study develops a marginal cost-based measure of APCRS, addressing the limited attention paid to cost-effectiveness in existing end-of-pipe approaches. While green total factor productivity (GTFP) mainly evaluates the overall efficiency of green agricultural production, it does not directly reveal the economic cost of reducing additional units of pollution or carbon emissions. In contrast, marginal cost analysis captures the cost trade-offs between agricultural pollution reduction and carbon mitigation, thereby allowing this study to assess whether the two environmental objectives can be jointly achieved at lower economic cost, which provides a more direct economic interpretation of APCRS; (2) this study systematically examines the impact of AIIA on APCRS, thereby extending the application boundary of research on AI and green transformation in the agricultural sector; (3) this study investigates the underlying mechanisms and moderating effects, highlighting the dynamic nature of this relationship; and (4) this study explores the regional heterogeneity and stage-specific effects of AIIA on APCRS.

2. Literature Review and Theoretical Hypotheses

2.1. Nonlinear Effect of AIIA on APCRS

The concept of "synergistic benefits" was proposed by the Intergovernmental Panel on Climate Change (IPCC), with the aim of reducing greenhouse gas emissions while simultaneously lowering other environmental pollutants and protecting biodiversity, thereby generating dual benefits and reducing the overall social cost of emission abatement. China has likewise attached great importance to improving the mechanism for coordinated pollution and carbon reduction. In agriculture, pollution reduction and carbon mitigation correspond, respectively, to improvements in agro-ecological environmental quality and the achievement of the "dual carbon" goals. Pollution reduction aims to decrease emissions of environmental pollutants such as those associated with agricultural non-point source pollution, whereas carbon mitigation focuses on curbing greenhouse gas emissions, including CO_2, to slow climate change [17]. The use of chemical inputs lies at the core of multiple environmental problems, and the underlying generation processes are closely intertwined. Consequently, compared with addressing these issues separately, joint abatement can more effectively enhance the synergistic performance of pollution reduction and carbon mitigation [18]. However, existing assessment approaches—such as the coupling coordination degree model and cross-elasticity measures of coordinated control—overlook the underlying economic mechanisms and cost–benefit considerations that are essential to sustainable green agricultural development. As a pillar of food security and the rural economy, agriculture can only achieve sustainable development when the economic system, the production system, and the environmental system are well coordinated. Accordingly, the quantitative assessment of APCRS should also be conducted from the perspective

of the full process of economic performance and output, rather than focusing solely on end-of-pipe emission reduction.

According to the "core–periphery" theory in new economic geography, the initial response to innovation is often the agglomeration of factors [19]. Compared with peripheral areas, core regions typically offer stronger development prospects and are therefore more attractive to innovative factors. As capital, talent, and information increasingly flow toward these core regions, a "Matthew effect" may emerge, widening development gaps and exacerbating the resource allocation disadvantages of peripheral actors. This regional imbalance can severely constrain the flow of innovative factors and, in the process of technology adoption, may give rise to information asymmetry among smallholders, thereby hindering the diffusion of green agricultural technologies. In addition, the initial costs of investing in green technologies are relatively high, and agricultural producers often have limited willingness or capacity to adopt new technologies. In China, agricultural production is still dominated by smallholders. When the level of agricultural industry agglomeration remains low, the promotion of green innovative technologies faces multiple constraints, including high costs, inefficient resource allocation, and difficulties in integrating the agricultural value chain. Under such conditions, the contribution of innovation to green development remains limited [20]. Moreover, green agricultural technologies are usually driven by research institutions and agribusinesses, and their diffusion and application often involve a substantial time lag [21]. To maintain agricultural output, farmers often continue to rely on extensive production methods, increasing the use of fertilizers, pesticides, and other chemical inputs, which in turn suppresses improvements in agricultural pollution and carbon mitigation. Taken together, the early stage of AIIA tends to intensify rural resource misallocation and slow the diffusion of green technologies.

While the core–periphery framework emphasizes the agglomeration of factors, balanced development theory and diffusion of innovations theory suggest that, in the long run, the diffusion of innovation across different stages, together with the mobility and profit-seeking nature of production factors, can eventually promote more balanced regional development. AIIA can generate economies of scale by improving factor allocation efficiency, while also enhancing the efficiency of green development through industrial upgrading and green technological progress [22,23]. The flow of technology and production factors may, in turn, induce agricultural producers to adopt new technologies and equipment more actively, thereby advancing the green agriculture transformation. Accordingly, the impact of AIIA on APCRS is likely to be more complex and dynamic than a simple linear relationship would suggest. Thus, this study proposes the following hypothesis:

H1. *There is a U-shaped relationship between AIIA and APCRS.*

2.2. Mediating Effect of TP

AI has brought disruptive changes to existing modes of technological innovation and may affect APCRS both directly and indirectly through multiple channels. The preceding discussion highlights the nonlinear and complex relationship between AIIA and APCRS, underscoring the need to further examine the mechanisms underlying this interaction. Industry agglomeration itself generates knowledge spillovers. Through the exchange of labor, products, and resources within agglomerated areas, new technologies can diffuse more rapidly, thereby influencing regional economic efficiency. Existing studies generally agree that technological progress and innovation are key drivers of agricultural green productivity [24–26]. AI promotes technological change and enhances society's capacity to monitor, adapt to, and respond to climate and environmental change [27]. Through the application of AI and automation technologies, the efficiency of natural resource use can be improved [28]. Industry agglomeration also attracts a large concentration of talent. When

more specialized personnel are engaged in environmental research and implementation, the development of low-carbon technologies can be accelerated. At the same time, industry agglomeration helps reduce the costs and risks of research and development, generating positive effects on technology diffusion and green transition. More specifically, AI can extract key information from big data and generate predictions, helping farmers identify problems, determine causal relationships, and improve decision-making capacity. In addition, intelligent services and products enhance the precision of farm management, thereby improving the efficient use of fertilizers and pesticides and reducing agricultural waste [29]. Thus, this study proposes the following hypothesis:

H2. *Technological progress (TP) partially mediates the relationship between AIIA and APCRS.*

2.3. Moderating Effects of SER, AL, and RII

To advance agricultural modernization and transformation, the Chinese government proposed in the Strategic Plan for Rural Revitalization (2018–2022), issued in 2018, that it would "vigorously cultivate new service providers and accelerate the development of one-stop agricultural producer services." As a result, agricultural socialized services (SER) have gradually evolved from a government-led arrangement into a service system jointly involving government agencies, rural cooperatives, and other actors, and have become a major organizational vehicle for the diffusion of green technologies. The technological spillovers generated by AIIA involve clear thresholds for effective use. If farmers lack adequate understanding of new green technologies, they may easily develop resistance or hesitation toward adoption, thereby lowering technology utilization and weakening APCRS. The effective provision of agricultural socialized services can significantly promote farmers' green production behavior, and this positive effect becomes even more pronounced as rural incomes rise [30]. At the same time, the adoption and diffusion of green technologies exhibit the presence of peer effects. Green behavior can function as a learning model for other farmers, and providing peripheral farmers with agricultural socialized services and related resources can further strengthen this peer effect [31]. Through technology extension, information support, and factor trusteeship, agricultural socialized services continuously improve the ecological efficiency of agricultural land. Therefore, as the level of agricultural socialized services increases, the negative impact of AIIA on APCRS may gradually weaken. The core of economic development lies in the mobilization and allocation of resources and production factors. The green modernization of agriculture likewise depends on the smooth flow of production factors and technology into the agricultural sector. Regions with higher agricultural labor productivity (AL) often also have more efficient agricultural resource allocation, allowing development momentum to shift toward technology-driven and green modern inputs [32]. The technological progress induced by AIIA entails a certain threshold, whereas regions with higher agricultural labor productivity are more likely to possess the foundations of technology-driven and large-scale operations. This enables technological progress to take effect more quickly. The agricultural modernization goals proposed by the Chinese government include not only improvements in green productivity, but also the development of a more complete agricultural industrial system and the deeper integration of primary, secondary, and tertiary industries in rural areas. Regional industrial integration (RII) promotes linkages among agriculture, processing, and services. On the one hand, it facilitates the resource utilization of agricultural waste and thus effectively reduces agricultural pollution. On the other hand, the integration of the three industries attracts substantial capital, highly skilled talent, and technology into rural areas, providing sufficient financial support and technical safeguards for the implementation of low-carbon agricultural projects and significantly advancing green agricultural development [33]. Because industrial integration is mainly

achieved by extending the industrial chain, upgrading the value chain, and improving the benefit-sharing chain, it strengthens the interest linkages among agricultural producers, participants in agricultural socialized service systems, and enterprises. In the process, it enhances the willingness of all parties to use new technologies to promote the green transformation of agriculture. Thus, this study proposes the following hypotheses:

H3a. *SER moderates the U-shaped relationship between AIIA and APCRS.*

H3b. *AL moderates the U-shaped relationship between AIIA and APCRS.*

H3c. *RII moderates the U-shaped relationship between AIIA and APCRS.*

The following mechanism diagram illustrates the logical relationship between the variables in this research, as shown in Figure 1.

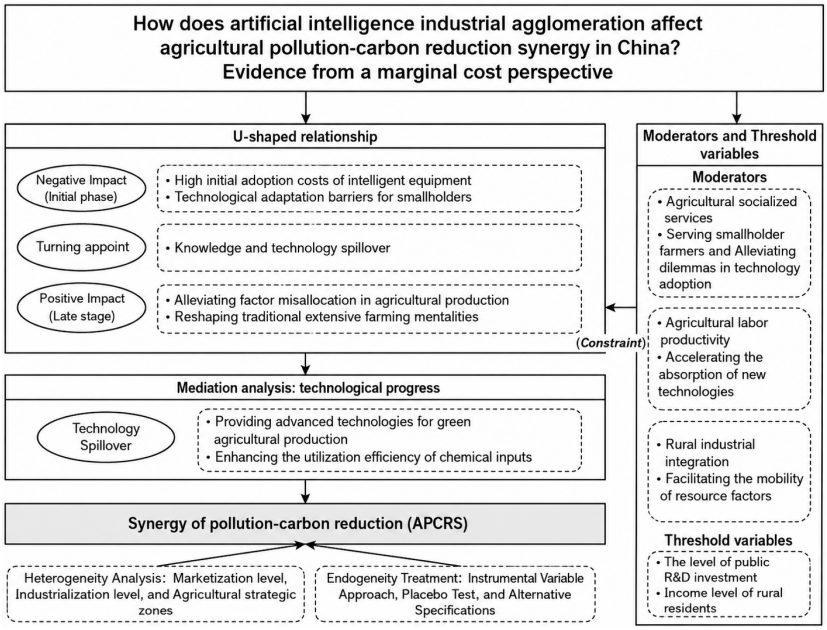


Figure 1. Analytical framework for the non-linear relationship between AIIA and APCRS.

3. Methodology and Data

This section describes the methodological framework and data construction process of the study. Section 3.1 introduces empirical models, including the baseline regression model, mediating effect model and moderating effect model, which are used to examine the direct effect, transmission mechanisms and boundary conditions between AIIA and APCRS. Section 3.2 explains the measurement of the core variables and control variables, with particular attention to the construction of APCRS from the marginal cost perspective and the measurement of AIIA. This section also presents the data sources, sample selection, the statistical procedures and software used to generate empirical results. These subsections provide the basis for the subsequent empirical analysis.

3.1. Model

3.1.1. Baseline Regression Model

Based on the theoretical analysis above, AIIA may have a nonlinear effect on APCRS. Therefore, this study first constructs a baseline regression model to identify the direct

relationship between AIIA and APCRS. Equation (1) specifies the baseline regression model used to examine the relationship between AIIA and APCRS.

$$APCRS_{i,t} = \alpha_0 + \alpha_1 AIIA_{i,t} + \alpha_2 AIIA_{i,t}^2 + \alpha_j Control_{i,t} + \gamma_i + \sigma_t + \varepsilon_{it}. \quad (1)$$

where APCRS denotes the level of agricultural pollution–carbon reduction synergy measured on the basis of marginal cost, while AIIA represents the level of artificial intelligence industry agglomeration. Control refers to a set of control variables. The subscripts i and t denote province and year, respectively; γ represents individual fixed effects, σ represents time fixed effects, and ε is the random error term.

3.1.2. Mediating Effect Model

Based on the diffusion of innovation [34], new ideas and technologies spread step by step. AIIA may boost technological advances, which in turn drive green growth in agriculture. On this basis, a mediation effect model within the framework of Model (1) is constructed, incorporating technological progress (TP) as a mediating variable. The mediation effect examination conducts an in-depth analysis of the influencing mechanisms between AIIA and APCRS. Equations (2) and (3) are used to examine whether technological progress serves as a mediating variable between AIIA and APCRS.

$$TP_{i,t} = \beta_0 + \beta_1 AIIA_{i,t} + \beta_2 AIIA_{i,t}^2 + \beta_j Control_{i,t} + \gamma_i + \sigma_t + \varepsilon_{it,} \quad (2)$$

$$APCRS_{i,t} = \varphi_0 + \varphi_1 AIIA_{i,t} + \varphi_2 AIIA_{i,t}^2 + \varphi_3 TP_{i,t} + \varphi_j Control_{i,t} + \gamma_i + \sigma_t + \varepsilon_{it.} \quad (3)$$

where $TP_{i,t}$ represents technological progress of province i in year t, and the meaning of other variables is consistent with the previous section.

3.1.3. Moderating Effect Model

Providing that the baseline regression measures the effect of AIIA on APCRS, this section further examines whether this effect varies under different agricultural development conditions, incorporating agricultural socialized services (SER), agricultural labor productivity (AL), and rural industrial integration (RII). These factors may influence the absorption and application of AI-related technologies [31,33,35] in agricultural production, strengthening or weakening the impact of AIIA on APCRS. Therefore, to identify the boundary conditions of the relationship between AIIA and APCRS, this study constructs Equation (4).

$$APCRS_{i,t} = a_0 + a_1 AIIA_{i,t} + a_2 AIIA_{i,t}^2 + a_3 W_{i,t} + a_4 AIIA_{i,t} W_{i,t} + a_5 AIIA_{i,t}^2 W_{i,t} + a_j Control_{i,t} + \gamma_i + \sigma_t + \varepsilon_{it}. \quad (4)$$

where $W_{i,t}$ represents agricultural socialized services, agricultural labor productivity, rural industrial integration, and the meaning of other variables is consistent with the previous section.

3.2. Variables and Data Description

3.2.1. Dependent Variable: Agricultural Pollution–Carbon Reduction Synergy

Agricultural non-point source pollution mainly includes three components: fertilizer application on farmland, solid agricultural waste from crop production, and livestock and poultry manure [36]. Given that different pollutants vary in their units of measurement and environmental damage intensity, this study adopts the pollution equivalent method [37] to construct a comparable indicator of pollution reduction in Equations (5) and (6).

$$NP = NP_{TN} + NP_{TP} + NP_{COD;} P_i = \sum_{m=1}^{3} Q_{im} \rho_{im} \varphi_{im}, \quad (5)$$

$$NP_i = P_i / C_i. \tag{6}$$

where NP denotes the three major sources of agricultural pollution: fertilizer application on farmland, solid agricultural waste from crop production, livestock and poultry manure. The specific pollutants involved include total nitrogen (TN), total phosphorus (TP), and chemical oxygen demand (COD). *NP* is then obtained by summing the standardized pollution loads of TN, TP, and COD. NP_i is the standardized pollution load of pollutant i, calculated by dividing P_i; P_i denotes the emission of pollutant i, where i includes TN, TP, and COD; Q_{im}, ρ_{im}, φ_{im} represent, respectively, the statistical quantity from the pollution inventory, the pollutant generation coefficient, and the loss rate of pollutant i from pollution source m. NP_i denotes the pollution equivalent discharge of pollutant i; C_i the standard concentration value of pollutant i based on the water quality control category under the water environmental functional zoning system [38]. The detailed parameters are provided in Appendix A. Drawing on the carbon emission accounting formulas developed in previous studies [39,40], this study constructs a formula for measuring agricultural carbon emissions, as shown in Equation (7).

$$CE = \sum_{i=1}^{n} CE_i = \sum_{i=1}^{n} T_i \times \omega_i. \tag{7}$$

where CE denotes the total carbon emissions [41] generated in each province, *i* represents the source of agricultural carbon emissions, and T_i denotes the actual amount of each carbon source. ω_i represents the emission coefficient of each carbon source, as reported in Appendix B.

According to previous research [42,43], agricultural pollution control and carbon reduction involve a production process where inputs, desirable outputs, and undesirable outputs coexist. Therefore, this study refers to a slack-based measure (SBM) model [44] with undesirable outputs and then solves its dual form. The data calculated based on Equations (5)–(7) are used as the values for the undesirable outputs. The main advantage of the SBM model is that it explicitly incorporates slack variables into the analytical framework, allowing different variables to change at different proportions. Following the environmental technology framework proposed [45] and the global benchmark technology introduced [46], this study constructs the production possibility set based on global benchmark technology under the assumption of constant returns to scale in Equation (8).

$$\begin{aligned}
&\rho = \min \frac{1 - \frac{1}{I}\sum_{i=1}^{I} \frac{s_i^x}{x_{i0}}}{1 + \frac{1}{S_1+S_2}\left(\sum_{m=1}^{S_1} \frac{s_m^p}{p_{m0}^t} + \sum_{k=1}^{S_2} \frac{s_k^b}{b_{k0}^t}\right)} \\
&\text{s.t.} \\
&\sum_{t=1}^{T}\sum_{n=1}^{N} \lambda_n^t x_{ni}^t + s_i^x = x_{i0}^t, \forall i, \\
&\sum_{t=1}^{T}\sum_{n=1}^{N} \lambda_n^t p_{nm}^t - s_m^p = p_{m0}^t, \forall m, \\
&\sum_{t=1}^{T}\sum_{n=1}^{N} \lambda_n^t b_{nk}^t + s_k^b = b_{k0}^t, \forall k, \\
&s_i^x \geq 0, s_m^p \geq 0, s_k^b \geq 0, \lambda_n^t \geqslant 0.
\end{aligned} \tag{8}$$

where *n* denotes the number of decision-making units, and i denotes the number of inputs used by each DMU. s_1 and s_2 represent the numbers of desirable outputs and undesirable

outputs in the model, respectively. x_{i0}, p_{m0}, and b_{k0} denote inputs, desirable outputs, and undesirable outputs, respectively. s_i^x, s_m^p, and s_k^b represent the slack variables associated with the i input, the m desirable output, and the k undesirable output, respectively. ρ is the objective function, and a value closer to 1 indicates a higher level of efficiency.

This study constructs a dual SBM model with undesirable outputs to quantify the marginal costs of pollution and carbon emissions. Since reducing undesirable outputs inevitably forces a decline in desirable outputs, the hidden cost of environmental governance can be measured by the marginal loss of desirable outputs—known as the shadow price [42,47]. Therefore, this study uses shadow prices, that is, the implicit marginal values of environmental factors or pollutant emissions derived from production technology constraints and optimization models—to measure the marginal effect of a one-unit change in these factors on desirable output. The shadow prices of undesirable outputs can be solved through the dual form of Equation (8). On this basis, Equation (9) presents the dual model used to derive the shadow prices in this study.

$$\max u_0^{\mathrm{p}} p_0^{\mathrm{t}} - u_0^{\mathrm{x}} x_0^{\mathrm{t}} - u_0^{\mathrm{b}} b_0^{\mathrm{t}}$$

s.t.

$$\begin{cases} u_0^{\mathrm{p}} P^{\mathrm{t}} - u_0^{\mathrm{x}} X^{\mathrm{t}} - u_0^{\mathrm{b}} B^{\mathrm{t}} \leqslant 0, \\ u_0^{\mathrm{x}} \geqslant \frac{1}{\mathrm{I}} \times \left(\frac{1}{x_0^{\mathrm{t}}} \right), \\ u_0^{\mathrm{p}} \geqslant \frac{1 + u_0^{\mathrm{p}} p_0^{\mathrm{t}} - u_0^{\mathrm{x}} x_0^{\mathrm{t}} - u_0^{\mathrm{b}} b_0^{\mathrm{t}}}{S_1 + S_2} \times \left(\frac{1}{p_0^{\mathrm{t}}} \right), \\ u_0^{\mathrm{b}} \geqslant \left(1 + u_0^{\mathrm{p}} p_0^{\mathrm{t}} - u_0^{\mathrm{x}} x_0^{\mathrm{t}} - u_0^{\mathrm{b}} b_0^{\mathrm{t}} \right) / (S_1 + S_2) \times \left(1 / b_0^{\mathrm{t}} \right). \end{cases} \tag{9}$$

where x_0^t denotes the input vector of the decision-making unit, p_0^t denotes the desirable output vector, and b_0^t denotes the undesirable output vector. X^t, P^t, and B^t represent, respectively, the input matrix, desirable output matrix, and undesirable output matrix of all units in period t. u_0^x, u_0^p, and u_0^b denote the virtual prices of inputs, desirable outputs, and undesirable outputs, respectively. I is the number of input indicators. Traditional SBM models are usually used to measure agricultural green total factor productivity (GTFP) or agricultural total factor productivity (ATFP). However, they can only evaluate agricultural production efficiency and cannot quantify the economic attributes of environmental factors. Therefore, from the perspective of marginal cost, this study constructs a dual SBM model based on the traditional SBM. Through the multiplier vector in the dual stage, we estimate the shadow prices of agricultural carbon dioxide and agricultural non-point source pollution, using them as their respective marginal abatement costs. This method provides a better integration of economic costs and emissions.

Based on Equation (9), assume that the shadow prices of desirable output and undesirable output are denoted by Q_p and Q_b, respectively. When estimating marginal abatement cost, the shadow price of desirable output is assumed to be equal to its market price [47], that is, $Q_p = 1$ yuan. MAC denotes the marginal abatement cost of undesirable output. Under this assumption, the shadow price of undesirable output, Q_b, can be expressed by Equation (10).

$$\mathrm{Q_b} = \mathrm{Q_p} \times \frac{u_0^{\mathrm{b}}}{u_0^{\mathrm{p}}} = \mathrm{MAC}. \tag{10}$$

Accordingly, this study defines the pollution–carbon reduction synergy as the weighted sum of the pollution reduction effect and the carbon reduction effect. The synergy effect is detailed in Equations (11)–(13):

$$\Delta C_{CE} = \frac{MACE_{CE} - MACT_{CE}}{MACE_{CE}}. \quad (11)$$

$$\Delta C_{NP} = \frac{MACE_{NP} - MACT_{NP}}{MACE_{NP}}. \quad (12)$$

$$APCRS = \alpha \times \Delta C_{CE} + \beta \times \Delta C_{NP}. \quad (13)$$

where $MACE_{CE}$ and $MACT_{CE}$ denote the marginal abatement costs of carbon dioxide under separate abatement and joint abatement, respectively, and ΔC_{CE} denotes the carbon reduction effect. $MACE_{NP}$ and $MACT_{NP}$ denote the marginal abatement costs of pollutants, respectively, and ΔC_{NP} denotes the pollution reduction effect. By simultaneously incorporating carbon dioxide and pollutants as two separate undesirable output dimensions into the dual SBM model specified in Equation (9), the model generates two dual variables for each pollutant, namely the dual variables associated with carbon dioxide and pollutants. Substituting these dual variables into Equation (10) yields the marginal abatement costs of carbon dioxide and pollutants under the joint-abatement setting, denoted as $MACT_{CE}$ and $MACT_{NP}$, respectively. By contrast, $MACE_{CE}$ and $MACE_{NP}$ are obtained using the same calculation steps. Specifically, carbon dioxide is introduced as the sole undesirable output to calculate $MACE_{CE}$, while pollutants are introduced as the sole undesirable output to calculate $MACE_{NP}$. When the two are assumed to be equally important, the parameter values are usually set as $\alpha = \beta = 0.5$. A weight-sensitivity check is provided in Appendix C.

3.2.2. Independent Variable: Artificial Intelligence Industry Agglomeration

This study uses AIIA as an independent variable. At present, there is still no unified definition of AIIA in the literature. According to the *Artificial Intelligence Development Report (2024)* issued by the China Academy of Information and Communications Technology, the development of AI depends on the advancement of both software and hardware. Therefore, this study primarily chooses the manufacturing of computers, communication equipment, and other electronic devices, as well as software and information technology services, to represent the AI industry. According to relevant literature [12], internet technologies significantly influence regional AI development through smart applications and innovation. Therefore, this study also includes 'internet and related services' as a component sector of the AI industry. *The Reference Table between the Classification of Strategic Emerging Industries and the International Patent Classification (2021)* also indicates that the AI industry encompasses equipment manufacturing, software development, and system integration services. Based on the above analysis, this study considers the AI industry to mainly involve three sectors: manufacturing of computers, communication equipment, and other electronic devices; internet and related services; and software and information technology services. In terms of measurement, this study first calculates AI industry employment in each province by summing the number of employees in the above three sectors. Then, following previous studies that use employment density to reflect the economic meaning of industrial agglomeration [48,49], AIIA is measured by the relative concentration of AI-related employment in each province, calculated as AI-related employment divided by the regional area. Specifically, a higher AIIA value indicates a higher employment density in AI-related industries within a province, reflecting a stronger level of artificial intelligence industry agglomeration.

3.2.3. Other Variables

Mediating Variable

To examine the impact of AIIA on APCRS, this study constructs a technological innovation index to measure technological progress. Technological progress is evaluated from two dimensions [50]—input and output—and the composite score is measured by a composite index constructed using the entropy method. (1) Input indicators include the number of research and development (R&D) personnel, the share of R&D expenditure in provincial GDP, and fixed asset investment in the primary industry. (2) Output indicators include the number of patent grants and the value of technology transactions.

Moderating Variables

Agricultural socialized services (SER) [51] are measured by the ratio of the output value of agriculture, forestry, animal husbandry, and fishery services to the total sown area of crops in each province. Agricultural Labor Productivity (AL) is calculated as the ratio of annual agricultural gross output to the number of agricultural laborers in each province [52]. Rural industrial integration (RII) is constructed by a composite index based on the entropy method [53]. The indicators include the share of agricultural product processing output value, the proportion of rural non-agricultural employment, rural e-commerce sales, and the share of leisure agriculture.

Control Variables

To isolate the effect of AIIA from other confounding factors, this study chooses certain control variables: (1) Fiscal support for agriculture is measured by the local fiscal expenditure on agriculture, forestry, and water affairs in total local general budget expenditure. (2) Share of value added in the primary is measured by the ratio of the primary industry's output value in regional GDP. (3) Environmental regulation, given the study period and data availability, is measured by sulfur dioxide emissions. (4) Digital infrastructure is measured by the ratio of the total length of long-distance optical cable lines to regional land area.

3.2.4. Data Sources

Thirty provinces (municipalities and autonomous regions) in China (excluding Hong Kong, Macao, Taiwan, and Tibet) from 2016 to 2024 are selected for the study. The data resources are the China Statistical Yearbook, China Rural Statistical Yearbook, China Labor Statistics Yearbook, China Population and Employment Statistics Yearbook, China Financial Statistics Yearbook, China Tertiary Industry Statistical Yearbook, provincial statistical yearbooks, and the National Bureau of Statistics of China. Missing values were handled using linear interpolation. The average share of interpolated observations across variables is 2.7%. Since 2024 is the final year of the sample period, the small number of missing values in 2024 was treated separately using endpoint imputation, with the corresponding observations replaced by the observed values from the preceding year. These imputed data account for 3.1% of the observations in the final year. When inconsistencies arose between the China Statistical Yearbook and provincial yearbooks, data from the latter were preferred. In the preprocessing stage, we winsorized key variables to reduce the impact of outliers and stabilize model estimations. All analyses were conducted in Stata 19.0. This study used a two-way fixed-effects model for baseline regression, verified robustness using instrumental variables, alternative variables, placebo tests, and mediation and moderation models. Finally, a threshold effect model was applied to test for the critical points. APCRS has a mean value of 0.631 and a standard deviation of 0.064 (Table 1). AIIA has a mean value of 2.303 and a standard deviation of 0.814, indicating substantial interprovincial variation

in AIIA. The descriptive statistics of the remaining variables are broadly consistent with existing findings and are therefore not discussed in detail.

Table 1. Summary statistics.

Variable	Definition	Unit	N	Mean	SD
APCRS	Agricultural pollution–carbon reduction synergy	Index	270	0.631	0.064
AIIA	Artificial intelligence industry agglomeration	Ratio	270	2.303	0.814
ER	Environment regulation	Count	270	13.825	11.886
AFI	Fiscal support for agriculture	Count	270	8.604	0.710
DIF	Digital infrastructure	Ratio	270	0.201	0.112
FIND	Share of value added in the primary	Ratio	270	0.033	0.021
TP	Technological Progress	Index	270	0.256	0.119
SER	Agricultural socialized services	Ratio	270	2.398	1.599
AL	Agricultural labor productivity	Ratio	270	1.882	1.832
RII	Rural industrial integration	Index	270	0.121	0.042

4. Results

4.1. The Level and Changing Trend of APCRS and AIIA

4.1.1. The Level and Changing Trend of APCRS

According to differences in grain supply–demand balance and grain output across provinces, China classifies its regions into three categories: major grain-producing regions, major grain-consuming regions, and grain-balanced regions. Overall, national APCRS was mainly concentrated in the range of approximately 0.50–0.70 during 2016–2024 (Figure 2), indicating that APCRS in most regions remained at a medium-to-high level. At the same time, a relatively weak shoulder peak appears on the left side of the distribution, suggesting that some regions still exhibited comparatively low levels of coordination. The main peak shows an overall tendency to shift rightward and become narrower. In the major grain-producing regions, a noticeable secondary peak is also observed, indicating that a small number of provinces remain in a lower-value group. The major grain-consuming regions display a wider distribution, a more pronounced rightward shift, and a clear right tail. The grain-balanced regions exhibit a narrower distribution, with no obvious tailing or extreme-value tendency.

4.1.2. The Level and Changing Trend of AIIA

Figure 3 presents the regional distribution of AIIA in China, where darker colors indicate higher levels of AIIA. From the spatiotemporal distribution maps, AIIA exhibits a clear spatial pattern characterized by "high in the east and low in the west." High-value regions are mainly concentrated in the eastern coastal area, parts of central China, and some southern provinces, whereas western China remains at relatively low levels in the early stage. Over time, however, the high-value regions gradually evolved from isolated points into more contiguous clusters. High-value areas expanded markedly in the central-eastern region and the southeastern coast, including Zhejiang and Guangdong. This suggests that the development of AI may exhibit a spatial diffusion effect. It is also worth noting that AIIA development remains relatively limited in northeastern and western China.

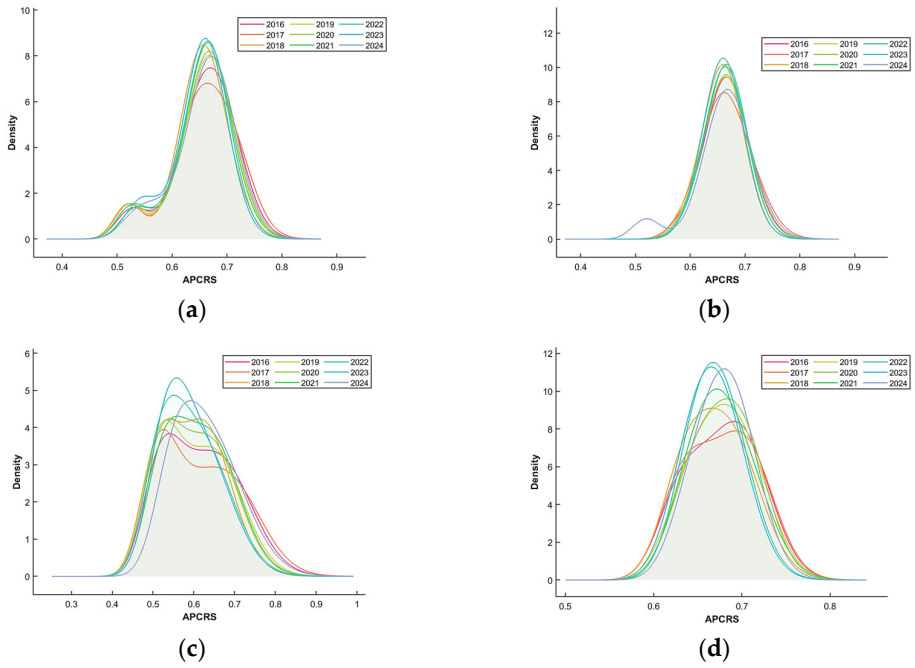


Figure 2. Kernel density curve of APCRS. Notes: (**a**) represents the full sample; (**b**) represents the major grain-producing regions; (**c**) represents the major grain-consuming regions; and (**d**) represents the grain-balanced regions.

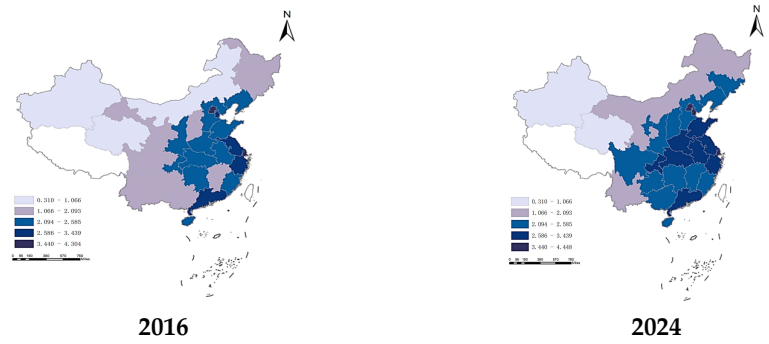


Figure 3. Spatial and temporal distribution of AIIA in 2016 and 2024. Note: The base map of the map is from the China National Bureau of Surveying and Mapping Geographic Information: GS [2019] 1822.

4.2. Effect of AIIA on APCRS

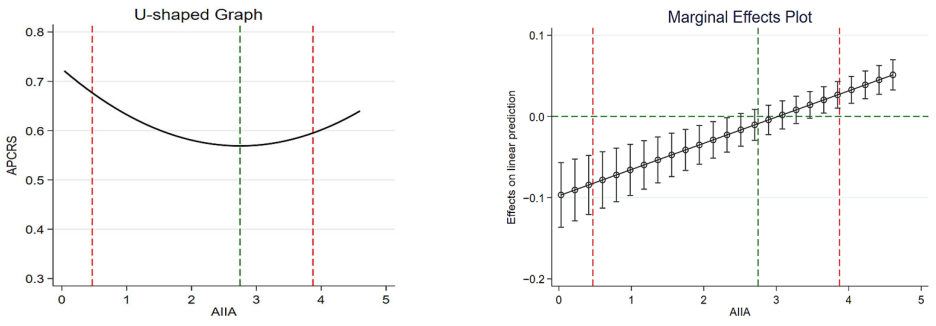
Tables 2 and 3 represent the benchmark regression and U-test results between AIIA and APCRS. Column (1) of Table 2 includes only the core explanatory variables, AIIA and $AIIA^2$, whose coefficients are significantly negative and positive, respectively, providing preliminary evidence of a U-shaped relationship. Columns (2) to (5) gradually introduce a series of control variables. Across these model specifications, the signs and statistical significance of AIIA and $AIIA^2$ remain unchanged. When testing for a U-shaped or inverted U-shaped relationship, it is easy to mistakenly interpret the significance of the squared term as sufficient evidence of such a pattern. To address this issue, this study uses the three-step procedure proposed [54] to determine whether a U-shaped relationship exists between AIIA and APCRS. This approach allows for a more rigorous assessment of the validity of the proposed nonlinear specification. First, as noted above, the quadratic term of AIIA is statistically significant and carries the expected sign. Second, the U-test reports the slope test results (Table 3), with the lower and upper bounds estimated at −0.113 and 0.077, respectively, both of which are significant at least at the 5% level. Third, the estimated

turning point is 2.749, and its 95% Fieller confidence interval is (0.469, 3.873), which lies entirely within the observed data range. The U-test results provide evidence consistent with a U-shaped relationship between AIIA and APCRS. As this interval covers a large part of the observed AIIA distribution, the turning point represents an estimated point at which the marginal association between AIIA and APCRS may change sign, rather than a precise policy threshold. The estimated marginal association between AIIA and APCRS is negative below the estimated turning point of 2.749 and positive above it, although this sign change should be interpreted with caution, given the wide Fieller interval. Using the estimated turning point as a reference, some provinces, such as Anhui, Beijing, and Zhejiang, appear to be located in the positive marginal association zone. Given the uncertainty surrounding the estimated turning point, the grouping across provinces is used only to describe the pattern observed in the sample and should not be treated as a strict policy boundary. The U-shaped curve and the corresponding marginal effect plot are presented in Figure 4.

Table 2. Benchmark regression results.

Variables	Dependent Variable: Agricultural Pollution–Carbon Reduction Synergy Effect (APCRS)				
	(1)	(2)	(3)	(4)	(5)
AIIA	−0.099 **	−0.116 ***	−0.103 ***	−0.077 ***	−0.114 ***
	(0.035)	(0.026)	(0.015)	(0.026)	(0.035)
$AIIA^2$	0.017 **	0.022 ***	0.038 ***	0.011 ***	0.021 ***
	(0.007)	(0.006)	(0.011)	(0.003)	(0.005)
ER	-	−0.006 ***	−0.009 **	−0.017 *	−0.005 *
	-	(0.002)	(0.004)	(0.009)	(0.003)
DIF	-	-	0.032 ***	0.025 ***	0.037 ***
	-	-	(0.007)	(0.004)	(0.007)
AFI	-	-	-	0.006	0.004
	-	-	-	(0.004)	(0.007)
FIND	-	-	-	-	−0.186
	-	-	-	-	(0.649)
Constant	0.634 ***	0.619 ***	0.617 ***	0.675 ***	0.682 ***
	(0.078)	(0.077)	(0.078)	(0.087)	(0.090)
N	270	270	270	270	270
Adj R^2	0.819	0.824	0.824	0.825	0.831
Year FE	YES	YES	YES	YES	YES
Province FE	YES	YES	YES	YES	YES

Notes: Standard errors are clustered at the provincial level and reported in parentheses; the same clustering scheme applies to all subsequent tables; ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.



(**a**) (**b**)

Figure 4. Visualization of the relationship between AIIA and APCRS. Notes: (**a**) shows the fitted U-shaped curve; (**b**) shows the marginal effect of AIIA on APCRS with confidence intervals. The green dashed line indicates the estimated turning point of AIIA. The red dashed lines indicate the lower and upper bounds of the 95% Fieller interval.

Table 3. U test results.

U Test	Lower Bound	Upper Bound
Slope	−0.113	0.077
P > |t|	0.019	0.006
Turning Point	2.749	-
95% Fieller interval	[0.469; 3.873]	-
Overall test	0.019 **	-

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

4.3. Robustness Test

To ensure the reliability of our baseline findings, this study conducts a series of rigorous tests to address potential endogeneity concerns and to assess the robustness of the identified U-shaped relationship between AIIA and APCRS.

Endogeneity Treatment. Although the fixed-effects model used in the baseline regression helps alleviate endogeneity to some extent, endogeneity arising from omitted variables or reverse causality may remain unavoidable. To address this issue, this study further employs the two-stage least squares (2SLS) method. Following the two-dimensional instrumental variable approach [55], the density of industrial robots across U.S. industries in 2004 (units per thousand workers) is used as the basis for constructing an instrument for AI development at the province–industry level in China. Specifically, this study decomposes U.S. industrial robot density in 2004 to the provincial level in China using the employment shares of industries within each province and then interacts this variable with the corresponding year dummies to form the instrumental variable. Because the baseline model includes both (AIIA) and ($AIIA^2$), the instrumental variables specification treats both terms as potentially endogenous. Accordingly, (AIIA) and ($AIIA^2$) are jointly instrumented by the Bartik instrument and its squared term, respectively. The relevance of the instrument is supported by the fact that China and the United States exhibited broadly similar industry trends in robot adoption during the study period. Therefore, U.S. industry-level robot density is expected to be correlated with the development of corresponding AI-related industries in China [56]. The exclusion restriction relies on the assumption that the 2004 U.S. industry-level robot density, interacted with predetermined provincial industry employment shares in China, affects provincial APCRS only through its association with AIIA, rather than through other unobserved provincial shocks. The use of predetermined 2004 provincial employment shares helps reduce concerns about contemporaneous reverse causality. In addition, province fixed effects, year fixed effects, and observable provincial controls are included to mitigate omitted variable concerns. Column (1) of Table 4 reports the results of the instrumental variable estimation. The K–P rk LM statistic is 50.392 and is significant at the 1% level, indicating that the null hypothesis of under identification is rejected. The C-D Wald-F statistic is 42.095, which exceeds the Stock–Yogo critical value at the 10% level, suggesting that the weak-instrument problem is not a concern and that the instrument is correlated with the endogenous variable. This indicates that the nonlinear association between AllA and APCRS remains consistent after accounting for potential endogeneity, further supporting the robustness of the baseline regression results.

Alternative Independent Variable. In this study, the AI industry is defined to include three sectors: manufacturing of computers, communication equipment, and other electronic devices; internet and related services; and software and information technology services. However, the manufacturing of computers, communication equipment, and other electronic devices also includes many labor-intensive rather than technology-intensive firms. To rule out the possibility that employment in labor-intensive firms affects the representativeness of the AIIA measure used in this study, this section reconstructs the AIIA index using

only employment in two sectors, internet and related services; software and information technology services, and denotes the new indicator as New AIIA. Column (2) of Table 4 reports the regression results based on this alternative measure. The results show that the linear term of New AIIA remains significantly negative at the 1% level, while the quadratic term remains significantly positive at the 1% level, consistent with the baseline regression.

Table 4. Regression results of robustness test.

Variables	Endogeneity Test	Variables	Alternative Independent Variable	Variables	Lagged Variable Model
	(1)		(2)		(3)
AIIA	−0.088 **	New AIIA	−0.131 ***	L.AIIA	−0.108 **
	(0.043)		(0.026)		(0.044)
$AIIA^2$	0.017 **	New $AIIA^2$	0.034 ***	L.$AIIA^2$	0.020 **
	(0.008)		(0.006)		(0.008)
ER	−0.011	ER	−0.019 **	ER	−0.008
	(0.007)		(0.008)		(0.005)
DIF	0.022 ***	DIF	0.043 ***	DIF	0.019 **
	(0.008)		(0.008)		(0.009)
AFI	0.011	AFI	0.004	AFI	0.001
	(0.008)		(0.004)		(0.005)
FIND	−0.149	FIND	−0.027	FIND	−0.436
	(0.599)		(0.645)		(0.718)
N	270	N	270	N	270
K-P rk LM	50.392 ***	Adj R^2	0.826	Adj R^2	0.814
C-D Wald-F	42.095	-	-	-	-
Year FE	YES	Year FE	YES	Year FE	YES
Province FE	YES	Province FE	YES	Province FE	YES

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

Lagged Variable Model: Considering that the empowering effect of AIIA on APCRS may exhibit a certain time lag, and to further eliminate potential endogeneity concerns, this study adopts the lagged variable model for robustness checks. Specifically, the core explanatory variable AIIA is lagged by one period ($t-1$) and then re-estimated. Column (3) of Table 4 reports the regression results based on this alternative measure. The results show that the linear term of L.AIIA remains significantly negative at the 5% level, while the quadratic term remains also significantly positive at the 5% level, consistent with the baseline regression.

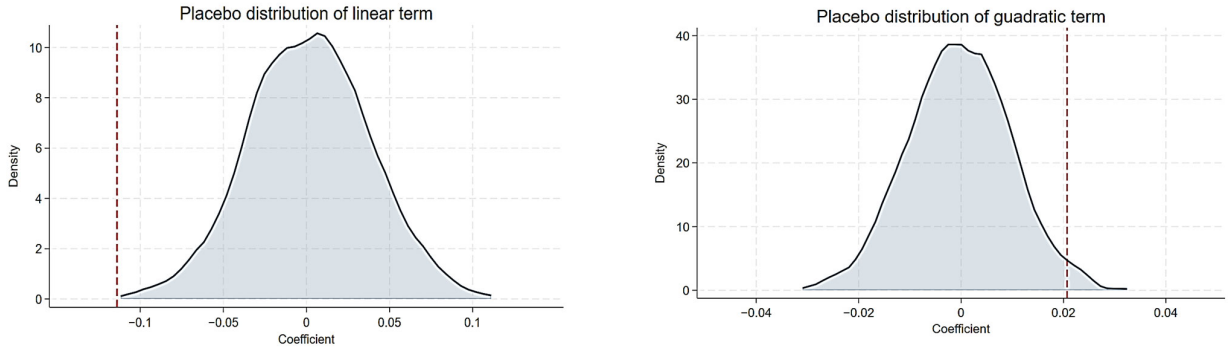
Spatial Durbin Model: Considering that AIIA and APCRS may exhibit spatial dependence across regions, the benchmark panel regression might overlook spatial correlations. To address this concern, this study further employs the Spatial Durbin Model (SDM) as a robustness check. Before estimating the SDM, this study also calculated the Global Moran's I, presented in Appendix D. The SDM main coefficients in column (1) of Table 5 show that the coefficient of AIIA is significantly negative, while the coefficient of $AIIA^2$ is significantly positive. This indicates that the U-shaped relationship between AIIA and APCRS remains valid after accounting for spatial dependence. The coefficient of W*AIIA is negative, while the coefficient of W*$AIIA^2$ is positive and statistically significant. This suggests that the AIIA level of neighboring provinces also has a nonlinear impact on local APCRS. Additionally, the estimated results for direct, indirect, and total effects all support the non-linear impact of AIIA on APCRS. This indicates that the U-shaped relationship exists not only in local effects but also in spatial spillovers and total effects.

Table 5. Estimation results and effect decomposition of the Spatial Durbin Model.

Variables	SDM Main	WX	Direct Effect	Indirect Effect	Total Effect
	(1)	(2)	(3)	(4)	(5)
AIIA	−0.102 ***	−0.152 **	−0.108 ***	−0.199 **	−0.307 ***
	(0.033)	(0.073)	(0.034)	(0.089)	(0.098)
$AIIA^2$	0.018 ***	0.043 **	0.018 ***	0.053 **	0.071 ***
	(0.007)	(0.018)	(0.007)	(0.021)	(0.024)
ER	−0.006 ***	0.002	−0.006 ***	0.001	−0.004
	(0.002)	(0.001)	(0.002)	(0.007)	(0.007)
DIF	0.142 **	0.035	0.146 ***	0.080	0.227
	(0.055)	(0.105)	(0.054)	(0.134)	(0.157)
AFI	−0.008 **	0.032 ***	−0.007 *	0.037 ***	0.030 ***
	(0.004)	(0.011)	(0.004)	(0.012)	(0.004)
FIND	1.306 **	−1.533	1.239 **	−1.653	−0.414
	(0.634)	(1.24)	(0.613)	(1.419)	(1.603)
N	270	-	-	-	-
ρ	0.181 **	-	-	-	-
Log-likelihood	703.169	-	-	-	-
R^2	0.4496	-	-	-	-

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

Placebo Test. To further exclude the potential influence of unobserved factors, this study constructs a placebo AIIA series using a Monte Carlo simulation. Figure 5 presents the kernel density distributions of the estimated coefficients for AIIA (left panel) and AIIA2 (right panel) from 1000 random simulations. The resulting placebo distributions, shown in blue, are tightly centered around zero. In contrast, the true coefficient estimates for the linear term (indicated by the red dashed line) are distinctly far from the simulated distributions. For the quadratic term, the estimated coefficient lies in the extreme tail of the distribution. These results collectively indicate that the estimated U-shaped relationship is not driven by unobservable random factors, reinforcing the robustness of our baseline findings.



(**a**) (**b**)

Figure 5. Placebo test. Notes: (**a**) reports the placebo distribution for the linear term of AIIA; (**b**) reports the placebo distribution for the quadratic term $AIIA^2$. Red dashed lines indicate the true estimated coefficients.

4.4. Heterogeneity Analysis

To examine the boundary conditions of the core findings, this study conducts a series of heterogeneity analyses. The results reported in Table 6 show that the level of marketization, the level of industrialization, and grain strategic zones all have significant effects on the estimated relationship.

Table 6. Results of heterogeneity analysis.

Variables	Levels of Marketization		Levels of Industrialization		Grain Strategic Zones	
	Low Marketization	High Marketization	Low Industrialization	High Industrialization	Main Grain-Producing Regions	Non-Main Grain-Producing Regions
	(1)	(2)	(3)	(4)	(5)	(6)
AIIA	0.251 **	−0.110 **	−0.121 **	−0.154 ***	−0.178 ***	−0.144 **
	(0.121)	(0.050)	(0.051)	(0.057)	(0.065)	(0.055)
$AIIA^2$	−0.103 **	0.020 **	0.019	0.023 **	0.061 **	0.021 **
	(0.044)	(0.009)	(0.014)	(0.010)	(0.027)	(0.009)
ER	−0.002	−0.008 **	−0.025 ***	−0.004	0.010 *	−0.014 **
	(0.003)	(0.004)	(0.009)	(0.015)	(0.005)	(0.006)
DIF	0.020	0.422 *	0.111	0.030	0.117	0.040
	(0.019)	(0.232)	(0.201)	(0.031)	(0.181)	(0.030)
AFI	0.003	0.017 **	0.016 **	0.006	0.010	0.011 **
	(0.004)	(0.007)	(0.007)	(0.014)	(0.009)	(0.005)
FIND	−1.292	−1.408	−2.077 **	−1.378	1.756	−2.699 *
	(0.858)	(1.052)	(0.976)	(0.981)	(1.710)	(1.457)
Constant	0.316 ***	0.840 ***	0.858 ***	0.808 ***	0.717 ***	0.957 ***
	(0.081)	(0.139)	(0.207)	(0.100)	(0.088)	(0.143)
N	122	148	135	135	117	153
Adj R^2	0.784	0.823	0.721	0.835	0.709	0.850
Year FE	YES	YES	YES	YES	YES	YES
Province FE	YES	YES	YES	YES	YES	YES

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

As regional differences in the level of marketization may affect factor mobility and resource allocation, this study further divides provinces according to their degree of marketization [57]. The corresponding regression results are presented in Columns (1) and (2) of Table 6. In the full sample, AIIA shows a U-shaped association with APCRS. However, this pattern is not uniform across regions with different levels of marketization. In regions with a low level of marketization, the coefficient on the linear term of AIIA is 0.251 and significant at the 5% level, while the coefficient on the quadratic term is −0.103. This indicates that in less marketized regions, AIIA may significantly suppress APCRS at a later stage. In regions with a high level of marketization, the coefficient on the linear term of AIIA is −0.110 and significant at the 5% level, while the coefficient on the quadratic term is 0.020, also significant at the 5% level.

Given that the level of industrialization may affect industrial linkages and the efficiency of technology diffusion, this study further conducts heterogeneity tests by industrialization level [58]. In Column (3), the coefficient on the linear term of AIIA is −0.121 and is significant at the 5% level, indicating that in regions with a low level of industrialization, AIIA exerts a significant inhibitory effect on APCRS at the initial stage. The coefficient on the quadratic term is 0.019; although positive, it is not statistically significant, indicating that the estimated nonlinear relationship is not clearly supported in regions with weaker industrial foundations. By contrast, in Column (4), the coefficient on the linear term of AIIA in highly industrialized regions is −0.154 and significant at the 1% level, while the coefficient on the quadratic term is 0.023 and significant at the 5% level, indicating a clear and robust U-shaped relationship between AIIA and APCRS.

In China, grain production is classified into major grain-producing regions, major grain-consuming regions, and grain-balanced regions based on factors such as geographic location and farming systems. In this study, regions are further grouped by agricultural functional orientation into major grain-producing regions and non-major grain-producing regions. In the major grain-producing regions, the coefficient on the linear term of AIIA is

−0.178 and significant at the 1% level, while the coefficient on the quadratic term is 0.061 and significant at the 5% level. In the non-major grain-producing regions, the coefficient on the linear term of AIIA is −0.144 and significant at the 5% level, while the coefficient on the quadratic term is 0.021, also significant at the 5% level.

4.5. Further Analysis

4.5.1. Analysis of Mediating Effect

After establishing the relationship between AIIA and APCRS, this study examines the mediating role of technological progress. Table 7 reports the regression results for technological progress as a mediator. Column (1) of Table 7 confirms the U-shaped relationship between AIIA and APCRS. In Column (2), with technological progress (TP) as the dependent variable, the linear term of AIIA is significantly negative, and the quadratic term is significantly positive, indicating that AIIA also has a nonlinear effect on technological progress. Column (3) presents the regression results after including the mediating variable TP. The coefficient of TP is significantly positive. At the same time, after TP is included, the coefficient on the linear term of AIIA becomes smaller than that in the full-sample regression, suggesting that technological progress plays a partial mediating role in the effect of AIIA on APCRS. Furthermore, to ensure the robustness of the mediation results, this study conducted further tests using the Bootstrap method, with 5000 bootstrap samples. The results are shown in Table 8. The test results indicate that the point estimate of the indirect effect is 0.016, with a 95% confidence interval of [0.0002, 0.0318]; the point estimate of the direct effect is −0.036, with a 95% confidence interval of [−0.0671, −0.0049]. Neither confidence interval includes 0.

Table 7. Mediating effect.

Variables	APCRS	TP	APCRS
	(1)	(2)	(3)
AIIA	−0.114 ***	−0.234 **	−0.105 ***
	(0.035)	(0.117)	(0.036)
$AIIA^2$	0.021 ***	0.147 ***	0.015 **
	(0.005)	(0.023)	(0.007)
TP	-	-	0.037 **
			(0.018)
Constant	0.750 ***	1.322 ***	0.692 ***
	(0.099)	(0.057)	(0.087)
Control Variables	YES	YES	YES
N	270	270	270
Adj R^2	0.824	0.813	0.829
Year FE	YES	YES	YES
Province FE	YES	YES	YES

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

Table 8. Bootstrap Autonomous Sampling 5000 Test Results.

Category	Effect	S.E.	z	$p > \|z\|$	95% Confidence Interval
Indirect effects	0.016	0.008	1.99	0.047	[0.0002, 0.0318]
direct effects	−0.036	0.016	−2.27	0.023	[−0.0671, −0.0049]

4.5.2. Analysis of Moderating Effect

After the above analyses, this study further turns to the more complex evolution of the U-shaped relationship between AIIA and APCRS by examining the moderating roles of SER, AL, and RII. It is hypothesized that these three factors do not eliminate the U-shaped

trajectory itself, but instead fundamentally alter its curvature and the timing of its turning point. To test this hypothesis, a series of models is constructed by introducing interaction terms between AIIA and its quadratic term and each of the three moderating variables.

The estimation results reported in Table 9 show that, in the models including agricultural socialized services and rural industrial integration, the coefficients on the linear interaction terms are significantly positive at least at the 5% level, while the coefficients on the quadratic interaction terms are significantly negative at least at the 1% level. This dual effect suggests that agricultural socialized services and rural industrial integration can both mitigate the initial siphoning effect associated with early-stage AIIA and stabilize the subsequent development of APCRS. By contrast, the coefficient on the linear interaction term with agricultural labor productivity is significantly negative at the 5% level, while the coefficient on the quadratic interaction term is significantly positive at the 5% level. This indicates that agricultural labor productivity strengthens the U-shaped relationship between AIIA and APCRS. These findings support Hypothesis 3.

Table 9. Moderating effect.

Variables	Agricultural Socialized Services	Agricultural Labor Productivity	Rural Industrial Integration
	(1)	(2)	(3)
AIIA	−0.130 **	−0.101 ***	−0.180 ***
	(0.050)	(0.038)	(0.049)
$AIIA^2$	0.026 ***	0.015 **	0.037 ***
	(0.008)	(0.007)	(0.011)
SER	−0.002		
	(0.003)		
AIIA * SER	0.006 **		
	(0.002)		
$AIIA^2$ * SER	−0.001 ***		
	(0.000)		
AL		0.008 **	
		(0.003)	
AIIA * AL		−0.025 **	
		(0.012)	
$AIIA^2$ * AL		0.012 **	
		(0.005)	
RII			0.216
			(0.156)
AIIA * RII			0.578 ***
			(0.184)
$AIIA^2$ * RII			−0.129 ***
			(0.037)
Constant	0.789 ***	0.759 ***	0.689 ***
	(0.102)	(0.136)	(0.105)
Control Variables	YES	YES	YES
N	270	270	270
Adj R^2	0.823	0.827	0.841
Year FE	YES	YES	YES
Province FE	YES	YES	YES

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

To better understand the economic meaning and dynamic implications of these moderating effects, this study further examines the shape of the U-shaped curve under different indicators. The specific results are reported in Table 10 and illustrated in Figure 6. First, as the levels of agricultural socialized services and rural industrial integration increase, the

effective curvature of the U-shaped curve declines significantly. By contrast, the curvature of the U-shaped relationship becomes significantly steeper as agricultural labor productivity rises. Figure 6 clearly illustrates these buffering and reinforcing effects under different indicators. Second, all three indicators accelerate the positive effect of AIIA on APCRS. As shown in Panel B of Table 10, at the mean level of each indicator, the turning point of the U-shaped curve shifts uniformly to the left relative to the baseline turning point of 2.749. Finally, this study compares the three indicators in greater depth. The results in Table 10 show that agricultural labor productivity exhibits the strongest accelerating effect, producing the largest leftward shift in the turning point, to 1.994. By comparison, agricultural socialized services and rural industrial integration generate only smaller leftward shifts at their mean levels, with turning points of 2.488 and 2.531, respectively. This indicates that agricultural labor productivity is a particularly effective channel for promoting green agricultural development. The turning points at the 75th percentile further show that the turning points associated with SER and AL both shift to the left, whereas the turning point associated with RII shifts to the right.

Table 10. Characteristics of the U-curve moderated by SER, AL and RII.

Variables	SER	AL	RII
Panel A: Curve Shape			
Curvature at Mean Level	0.046	0.074	0.044
Change in curve shape	Flatter	Steeper	Flatter
Panel B: Turning Point			
Baseline Turning Point	2.749	2.749	2.749
Turning Point at Mean Level	2.488	1.994	2.531
Movement vs. Baseline	Leftward	Leftward	Leftward
Turning Point at Low Level (p25)	2.493	2.310	2.489
Turning Point at High Level (p75)	2.489	1.939	2.568
Movement (p25 → p75)	Leftward	Leftward	Rightward

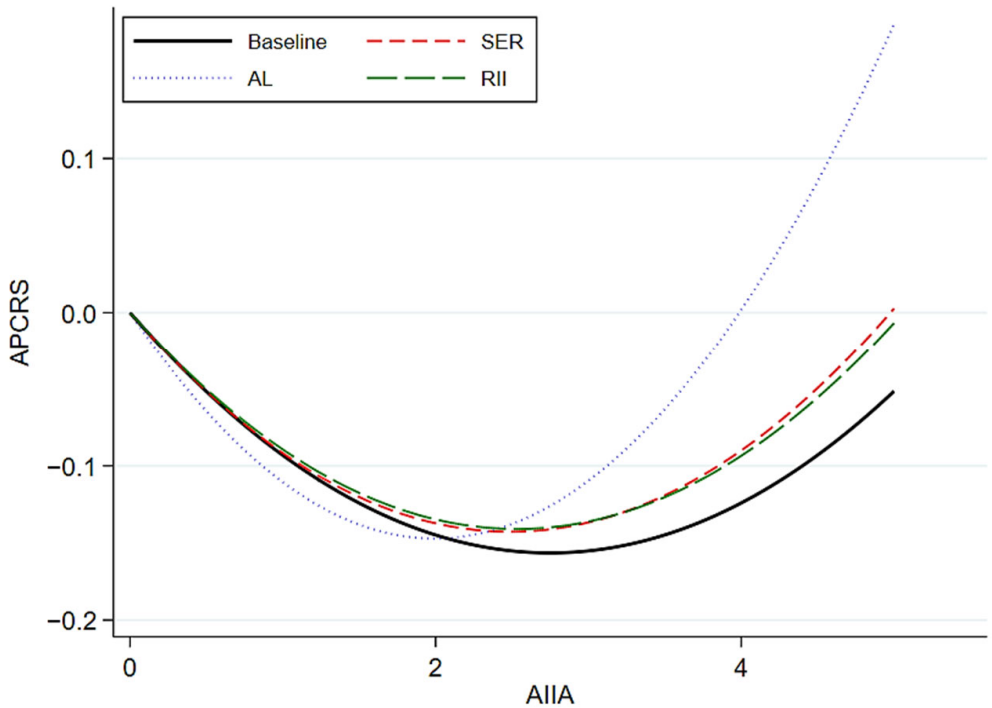


Figure 6. The moderating effect of SER, AL and RII.

4.5.3. Threshold Effect Analysis

This study confirms the existence of a robust average U-shaped relationship between AIIA and APCRS. This finding raises a deeper question: is the U-shaped effect an inherent economic pattern, or does it depend on specific development conditions? To further verify the presence of structural nonlinearity, this study employs a panel threshold regression model and uses two relevant indicators as threshold variables: rural residents' income level and the level of public R&D investment. The threshold values are identified through a grid search procedure [59], and their statistical significance is evaluated using 2000 bootstrap replications. The threshold test results are reported in Table 11. For rural residents' income, the single-threshold effect is statistically significant at the 5% level, with an estimated threshold value of 1.628. For public R&D investment, the estimated threshold value is 0.026. The likelihood ratio (LR) function plots in Figure 7 provide visual support for these results, as the LR statistics at each estimated breakpoint fall below the critical value line, confirming both the existence and the significance of the thresholds. Column (1) of Table 12 reports the results when income is used as the threshold variable. At low-income levels (Income $\leq$ 1.628), AIIA has only a significant positive quadratic effect on APCRS. However, once income exceeds the threshold (Income > 1.628), the relationship shifts to the conventional U-shaped pattern. Column (2) reports the threshold regression results for public R&D investment. At low levels of public R&D investment (PRI $\leq$ 0.026), the effect of AIIA on APCRS is significantly negative and linear, with no evidence of a positive quadratic mechanism. Once the threshold is crossed (PRI > 0.026), a structural shift emerges, and the relationship evolves into a statistically significant U-shaped pattern.

Table 11. Results of threshold estimation.

Threshold Variable	Threshold Number	Threshold Value	*p*-Value	95% Conf. Interval (Lower Limit)	95% Conf. Interval (Upper Limit)
Income	The first threshold	1.628	0.036	1.593	1.689
PRI	The first threshold	0.026	0.074	0.025	0.026

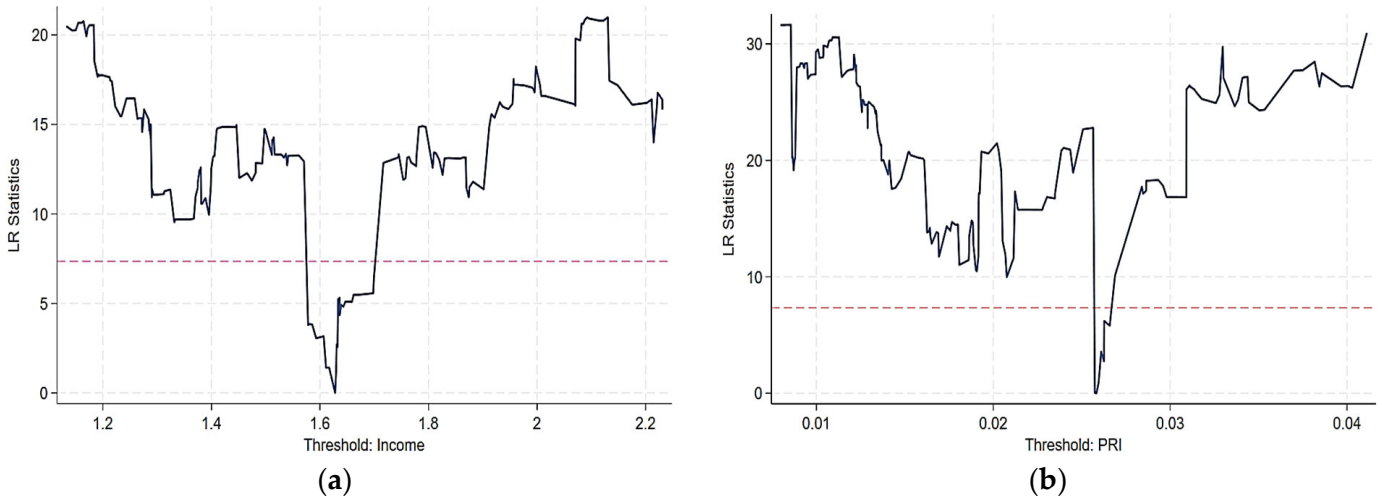


Figure 7. The result of the LR-test. Notes: (**a**) reports the threshold test for rural residents' income; (**b**) reports the threshold test for public R&D investment. The red dashed line represents the critical value of the LR statistic at the 5% significance level.

Table 12. Results of the threshold effect.

Variables	Rural Residents' Income Level (Income)	Public R&D Investment (PRI)
	(1)	(2)
AIIA (Income $\leq$ 1.628)	−0.057	-
	(0.043)	-
$AIIA^2$(Income $\leq$ 1.628)	0.022 *	-
	(0.012)	-
AIIA (Income > 1.628)	−0.070 **	-
	(0.034)	-
$AIIA^2$(Income > 1.628)	0.014 **	-
	(0.007)	-
AIIA (PRI $\leq$ 0.026)	-	−0.059 *
	-	(0.035)
$AIIA^2$(PRI $\leq$ 0.026)	-	0.001
	-	(0.009)
AIIA (PRI > 0.026)	-	−0.112 ***
	-	(0.033)
$AIIA^2$(PRI > 0.026)	-	0.019 ***
	-	(0.006)
Constant	0.665 ***	0.746 ***
	(0.103)	(0.095)
Control Variables	YES	YES
N	270	270
Adj R^2	0.833	0.844
Year FE	YES	YES
Province FE	YES	YES

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

5. Discussion

(1) The U-shaped relationship reveals a dynamic two-stage response of AIIA to APCRS. This finding shows that the impact of AI industrial development is not a steady, continuous boost, but instead involves a 'technological pain period.' In the initial stage, a mismatch of production factors may lead to a temporary negative effect on green agricultural development. However, as the level of AIIA increases beyond the estimated turning point, it becomes associated with more favorable APCRS outcomes. Some regions, such as Beijing and Zhejiang, gather a wealth of scientific talent, agri-tech enterprises, and research institutions. Such relatively comprehensive R&D supply chains, in turn, lower the entry barrier for agricultural practitioners and bolster both their willingness and ability to implement intelligent technologies. This transformation is also consistent with the Environmental Kuznets Curve (EKC), in which technological effects contribute to environmental improvement. Our findings extend the strictly linear results reported in previous studies. Although two distinct strands of literature suggest, on the one hand, that AI development linearly enhances agricultural eco-efficiency [60] and, on the other hand, that it may have a negative effect on energy efficiency [61], neither strand has accounted for the potential nonlinear externalities of the AI industry. This study argues that the nonlinear pattern identified here is closely related to the distinctive characteristics of the agricultural sector. Unlike manufacturing and urban industries, agriculture in China is still dominated by traditional smallholders, and with the continued outflow of effective rural labor, many agricultural producers have relatively low levels of education and limited capacity to absorb new technologies. When capital and digital resources may be drawn into non-agricultural sectors [62], AI-related technologies have not yet been effectively diffused into agricultural production. However, as technological barriers decline and policy support encourages producers to adopt new

technologies, the green development of agriculture begins to recover and grow. This study estimates an approximate turning point of the U-shaped relationship. However, given the wide Fieller confidence interval, it should be emphasized that the figure of 2.749 is context-dependent and should not be generalized.

(2) In addition, the heterogeneity results suggest that openness plays an important boundary role in shaping the nonlinear relationship between AIIA and APCRS. Previous research suggests that, in groups with lower degrees of marketization, industrial collaborative agglomeration exerts a blocking effect on green innovation efficiency, as resource misallocation and underdeveloped scale economies hinder the diffusion of green technologies [63]. This study is consistent with this argument, but also extends it by revealing a nonlinear relationship in green agriculture development. In low-marketization regions, AIIA is positively associated with APCRS at the initial stage, which may reflect short-term efficiency gains from the introduction of AI-related resources. However, as AIIA further increases, limited marketization may constrain capital mobility and market competition. Under such conditions, a constraint effect associated with agglomeration may gradually dominate the positive spillover effects, leading to an inverted U-shaped relationship. In less industrialized regions, AIIA may remain weakly connected to agricultural production and environmental governance. There is a nonlinear synergy: once industrialization surpasses a threshold, the positive impact of artificial intelligence on carbon emission efficiency intensifies significantly [64]. This study also indicates that the technological advantages of industrial agglomeration may not be effectively transformed into green agricultural development in low-industrialization regions. This is potentially because these areas suffer from limited supporting resources to absorb and internalize new technologies. These findings indicate that the effect of AIIA on APCRS is not universal, but marketization and industrialization affect the curvature of the relationship between AIIA and APCRS.

(3) Technological progress partially mediates the U-shaped relationship between AIIA and APCRS. This finding suggests that technological progress represents an important but non-exclusive mechanism through which AIIA is associated with APCRS. It also points to the existence of other parallel channels, such as technology costs and agricultural structural optimization. From the perspective of carbon mitigation, previous studies have shown that AI, represented by industrial robots, can promote carbon reduction in China through technological progress [65]. At the same time, this study extends the relevant literature [66,67] by supporting the mediating role of technological progress in the relationship between artificial intelligence industries and the marginal cost of achieving green agriculture. It is imperative to note that technological progress is a necessary but not a sufficient condition. Green development cannot rely solely on technological advancements while overlooking other critical supporting frameworks.

(4) Agricultural socialized services are a key foundation for the scaling-up and modernization of agricultural production. Such services can integrate new technologies into agricultural production activities and help smallholders access modern production technologies [68]. These findings suggest that socialized services are an important condition for transforming AIIA into green agricultural production capacity. From the perspective of labor as a production factor, agricultural producers in regions with higher labor productivity are better positioned to absorb the benefits of new technology [32]. Such regions are often characterized by more efficient agricultural resource allocation and a higher level of agricultural modernization. These conditions make it easier for AI-related technologies to be embedded in agricultural production processes, such as intelligent irrigation. Artificial intelligence is often associated with Industry 4.0, which involves various sectors such as logistics and processing. Regions with better rural industrial integration provide a stronger platform for Industry 4.0, which is often associated with a higher likelihood of adopting

and utilizing AI in agriculture. In summary, regions with a stronger technological base and more complete supporting service systems are able to realize the synergistic effects of AI on APCRS at an earlier stage.

(5) As an important manifestation of innovative technology, the AI industry requires a supportive innovation environment. In agriculture, however, credit access is often constrained, and technological innovation frequently suffers from insufficient funding and weak competitiveness. As a result, agricultural technological progress depends heavily on public R&D investment to drive innovation in the sector. Under such conditions, when the scale of public R&D investment is relatively large, the transformation and diffusion of green agricultural innovations show an accelerating trend. In addition, the green equipment associated with AI involves substantial adoption costs. When rural residents' income levels are low, higher production costs may discourage agricultural producers from actively adopting green production technologies. Once these conditions improve, however, technological diffusion associated with AIIA may contribute to the upward segment of the U-shaped relationship.

6. Conclusions and Policy Implications

6.1. Conclusions

Using panel data for 30 provinces in China from 2016 to 2024, this study examines whether and how AIIA affects APCRS from a novel perspective of marginal cost. (1) From the perspective of marginal cost, the average value of China's overall agricultural pollution and carbon reduction synergy effect was 0.63 during the sample period. In terms of evolution trends, this synergy effect shows a gradually increasing trend. However, a significant gap in the synergy level is observed among provinces located in the major grain-producing areas. (2) The full-sample results suggest a U-shaped association between AIIA and APCRS, and this finding remains consistent after accounting for endogeneity and conducting a series of robustness checks. The U-shaped response also exhibits different patterns across the heterogeneity analyses by marketization level, industrialization level, and grain strategic zones. Particularly, low-marketization regions show an inverted U-shaped pattern. This contrast suggests that regional marketization may serve as an important boundary condition for the non-linear effect of AIIA. (3) The mediation results indicate that technological progress partially mediates the U-shaped relationship between AIIA and APCRS. This suggests that technological progress is one important mechanism, but other pathways may also exist. (4) Regarding the moderating effects, agricultural socialized services, agricultural labor productivity, and rural industrial integration all significantly reshape the relationship between AIIA and APCRS. Notably, this nonlinear relationship is more pronounced in regions characterized by higher agricultural labor productivity. (5) The threshold analysis shows that the U-shaped relationship is not universally applicable, but conditional. It is activated when the level of public R&D investment and the income level of rural residents exceed certain critical thresholds, highlighting the crucial role of regional innovation support and farmers' income in shaping the relationship between AIIA and APCRS. Overall, this study contributes to the literature by linking AIIA with APCRS and by introducing a marginal cost perspective into the measurement of coordinated abatement performance.

Despite the meaningful exploration of AIIA and APCRS presented in this study, this study also has several limitations. First, although the SDM is used to examine the spatial robustness of the relationship between AIIA and APCRS, the mediation, moderation, threshold, and heterogeneity analyses are estimated within the non-spatial fixed-effects framework. Therefore, future research should develop integrated spatial models to examine the causal mechanisms while incorporating spatial spillover effects. Second, due to

constraints in data availability, the analysis is limited to provincial-level data. Expanding the sample to cover a broader range of regions would significantly improve the generalizability and applicability of the findings. Third, this study focuses on AIIA, while offering only limited evidence on the direct use of AI in agricultural production processes. Future research based on micro-level survey data and continuous tracking would help uncover the long-term dynamic mechanisms through which AI development affects green agriculture, which is crucial for promoting the green transformation of modern agriculture.

6.2. Policy Implications

Based on the empirical findings, this study offers the following main policy implications.

(1) A dynamic risk management strategy should be implemented. To address the initial downward phase of the U-shaped curve, the government should establish transitional support mechanisms, such as stabilization funds or targeted subsidies, to help farmers adopt green production technologies and reduce the adjustment costs associated with early-stage AIIA.

(2) The agricultural socialized service system should be further improved to facilitate the circulation of technological factors. Although this system continues to improve, some regions still face significant imbalances in terms of the scale of service organizations, technological maturity, and degree of specialization. Policymakers should therefore support the development of region-specific agricultural socialized service systems based on local agricultural conditions. Given the educational constraints faced by many agricultural producers, particular emphasis should be placed on providing smallholders with technical and financial support so as to increase their willingness and capacity to adopt new technologies.

(3) Market-oriented reforms should be deepened in less developed regions. Since technology diffusion depends on smooth channels for factor mobility, these regions should reduce barriers to the movement of factors and activate the channels through which technological progress can spread. Improving the institutional environment for factor mobility and market-based resource allocation is particularly important for transforming AIIA into agricultural green development outcomes.

(4) Attract social capital while reducing farmers' learning costs for green technologies. For regions where public R&D investment remains below the threshold, policy should prioritize increasing stable public R&D funding, improving agricultural green innovation platforms, and mobilizing other capital investments. Regions with low R&D investment may have weak innovation capabilities. Therefore, the critical step is to learn from more innovative areas. For regions where rural household income remains below the threshold, policy should focus on reducing the cost of technology adoption by expanding agricultural subsidies, improving rural financial services, and supporting the extension of agricultural value chains.

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Appendix A

Following the Environmental Quality Standards for Surface Water (GB3838-2002) [69], this study uniformly adopts the Class III standard concentrations—COD: 20 mg/L, TN: 1.0 mg/L, and TP: 0.2 mg/L—to calculate the absolute pollution equivalent discharge of TN, TP, and COD from each pollution source. The formulas and coefficients used for each pollution source are reported in Table A1.

Table A1. Formulas and coefficients for each pollution source.

Category	Pollution Generating	Unit	Emission Inventory	Formulas	Parameter Sources
Agricultural chemical fertilizer	Nitrogen fertilizer, phosphorus fertilizer, compound fertilizer	10 k tons	CON, D, P	Purified application amount * loss rate of fertilizers	The First National Pollution Source Census: Manual of Fertilizer Loss Coefficients for Agricultural Pollution Sources (2010)
Farmland solid waste	Rice, wheat, corn, beans, tubers, rapeseed	10 k tons	CON, D, P	Crop output * straw yield coefficient * (1 − comprehensive straw utilization rate) * straw nutrient content * loss coefficient	Statistical Yearbooks of Provinces (Autonomous Regions and Municipalities), Technical Materials from the Agricultural Pollution Census, and Related Literature
Livestock and poultry breeding	Cattle, sheep, pigs, and poultry	10 k tons	CON, D, P	Livestock and poultry production * excretion coefficient * loss coefficient	National Survey on Pollution from Large-Scale Livestock and Poultry Breeding and Countermeasures for Its Prevention and Control; Emission Standard of Pollutants for Poultry Breeding Industry

Notes: * denotes the multiplication.

Appendix B

Table A2. Emission coefficients for each carbon source.

Source	Carbon Emission Coefficient	Reference
Fertilizer	0.8956 kg·kg^{-1}	Oak Ridge National Laboratory (ORNL)
Pesticide	4.9341 kg·kg^{-1}	Oak Ridge National Laboratory (ORNL)
Agricultural film	5.18 kg·kg^{-1}	The College of Resources and Environmental Sciences (CRES), Nanjing Agricultural University
Diesel	0.5927 kg·kg^{-1}	The Intergovernmental Panel on Climate Change (IPCC)
Tillage	312.6 kg·hm^{-2}	College of Biological Sciences, China Agricultural University
Irrigation	20.476 kg·hm^{-2}	Relevant literature [70]

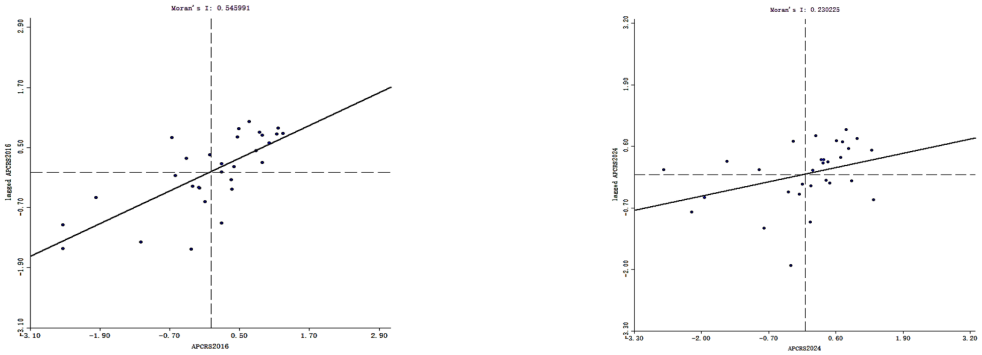
Appendix C

Table A3. Weight-sensitivity test for APCRS construction.

Variables	Baseline 0.5/0.5	Carbon-Oriented 0.7/0.3	Pollution-Oriented 0.3/0.7
AIIA	−0.114 ***	−0.107 ***	−0.084 ***
	(0.035)	(0.043)	(0.032)
AIIA^2	0.021 ***	0.015 **	0.016***
	(0.005)	(0.008)	(0.006)
Controls	YES	YES	YES
Constant	0.634 ***	0.691 ***	0.567***
	(0.078)	(0.098)	(0.091)
N	270	270	270
Adj R^2	0.819	0.782	0.675
Year FE	YES	YES	YES
Province FE	YES	YES	YES

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

Appendix D



(**a**) (**b**)

Figure A1. Global Moran's I scatter plots of APCRS in 2016 and 2024. Notes: (**a**) shows the Global Moran's I scatter plot of APCRS in 2016, and (**b**) shows the Global Moran's I scatter plot of APCRS in 2024.

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