Artificial Intelligence and Agricultural Pollution in China: A Firm-Level Nonlinear Analysis

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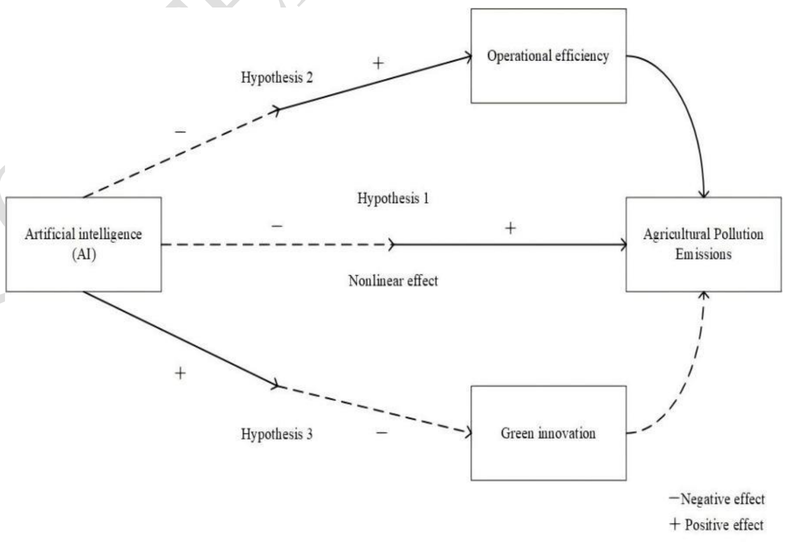
Abstract

Artificial intelligence (AI) promotes high-quality development in agriculture while also introducing new challenges for the management of pollutant emissions. This study aims to explore the pathways and underlying mechanisms through which AI influences agricultural pollutant emissions. To achieve this, the study employs data from Chinese publicly listed agricultural firms from 2010 to 2022 and conducts an empirical analysis using a semi-parametric additive model. The results show that artificial intelligence has a nonlinear effect on agricultural pollutant emissions, initially inhibiting them and subsequently promoting them. In the early stages of digitalization, constrained by limited resources, AI investment reduces the scale of production, thereby lowering pollutant emissions. However, as AI investment intensifies, firms overcome resource constraints, and the resulting productivity gains and scale expansion effects lead to increased emissions. The mechanism analysis further reveals that AI influences agricultural pollutant emissions through two main channels: it first decreases and then enhances firms' operational efficiency, and it initially boosts but later weakens their green innovation capacity. These findings provide theoretical support and practical guidance for promoting sustainable development and intelligent transformation in the agricultural sector.

Graphical abstract:



Keywords: Artificial intelligence；Agricultural pollutant emissions; Nonlinear effect; Operational efficiency; Green innovation

1. Introduction

As a fundamental sector of the national economy, agriculture plays a vital role in global food security, rural development, and ecological management, making it crucial to human livelihoods (Hou et al. 2024). With the rapid advancement of agricultural modernization, activities such as the use of chemical fertilizers and pesticides, livestock farming, and agricultural mechanization have increased significantly. These developments make agriculture one of the major sources of air and water pollution (Kuttippurath et al. 2024; Elahi et al. 2024). As the world's largest agricultural country, China accounts for nearly 30% of global nitrogen, phosphorus, and potassium fertilizer use over the past five years. This extensive use not only raises serious environmental pollution risks but also exerts considerable influence on global ecosystems and environmental governance. Therefore, investigating pollutant emissions from Chinese agricultural enterprises constitutes a critical component of global environmental governance and climate action, while also offering practical insights for developing countries undergoing rapid agricultural modernization and industrialization. Against the backdrop of the rapid development and widespread application of artificial intelligence (AI), several critical questions arise: Can AI effectively reduce pollutant emissions from Chinese agricultural enterprises? What specific patterns or characteristics does its impact on agricultural pollutant emissions exhibit? Through which mechanisms does AI exert its influence? Addressing these questions not only deepens our understanding of the relationship between AI and sustainable development, but also provides theoretical support and policy implications for promoting green transformation and intelligent governance in agriculture.

AI, characterized by autonomous learning, dynamic adaptation, and high-speed processing, is increasingly applied to agricultural activities (Oliveira and Silva 2023). Some studies employ AI technologies—such as machine learning, deep learning, and image recognition—to analyze and predict changes in pollutant emissions (Liu et al. 2025; Rahaman et al. 2025; Senthil Rathi et al. 2025). Other research suggests that AI's capabilities for automatic discovery and optimization offer new opportunities to address global climate and environmental issues (Chen et al. 2024; Zhou et al. 2024). First, AI enhances the efficiency of resource allocation in agricultural economic activities through its dynamic optimization capabilities, which improves energy use efficiency and productivity and thereby reduces pollutant emissions (Shen and Zhang 2023). Second, it reduces the barriers to knowledge acquisition for agricultural firms, facilitates skill complementarity among R&D personnel, and enhances research efficiency and green innovation capacity. According to Li et al. (2025), as firms strengthen their green technological capabilities, their pollutant emissions during the production process significantly decrease.

However, whether AI can effectively reduce pollutant emissions from agricultural enterprises remains an open question. On the one hand, the widespread application of AI in agricultural production enhances productivity but may also lead to the expansion of agricultural activities. This expansion effect can result in increased pollutant emissions. Overall, the environmental impact of AI depends on its net effect (Zhu et al. 2023). On the other hand, although AI lowers the barriers to acquiring knowledge and information—thereby facilitating the improvement of green innovation capacity in agricultural firms—an excess of information may trap firms in an "innovation trap," ultimately weakening their green innovation performance. Therefore, the impact of AI on agricultural pollutant emissions remains uncertain. Although some studies have acknowledged the possibility of nonlinear effects of AI (Shen and Zhang 2023; Lee and Yan 2024), few have examined the specific pathways through which AI affects pollutant emissions in the agricultural sector. Moreover, the underlying mechanisms of such impacts have yet to be systematically analyzed.

To fill this research gap, this study uses data from Chinese listed agricultural firms between 2010 and 2022 and employs a semi-parametric additive model to systematically analyze the impact of AI on agricultural pollutant emissions. Based on the findings, we propose relevant policy recommendations. This study makes three main contributions to the literature:

(1) Although existing literature acknowledges a correlation between AI and pollutant emissions, few studies provide a detailed analysis of the underlying impact pathways and characteristics, particularly in the context of China's agricultural sector. In response, this study applies a semi-parametric additive model—a nonlinear analytical approach—to examine the stage-dependent and nonlinear characteristics of AI's impact on pollutant emissions.

(2) This study explores the specific mechanisms through which AI affects agricultural pollutant emissions. Given the complexity of AI applications in agricultural practices, we consider the dynamic and heterogeneous effects of AI on firms' operational efficiency and green innovation capacity. This approach facilitates a better identification and understanding of the internal mechanisms through which AI influences pollution levels.

(3) Drawing on the empirical findings, we propose concrete and feasible policy recommendations. In doing so, this study contributes to the theory on AI's impact pathways and mechanisms in reducing agricultural pollutant emissions, and provides practical guidance for policymakers.

After the introduction, the remainder of the paper is structured as follows: Sect. "Literature review" reviews the relevant literature and identifies the existing gaps. Sect. "Mechanism analysis and research hypotheses" analyzes the direct effects of AI on pollutant emissions in agricultural enterprises and investigates the underlying transmission pathways. Sect. "Research design" presents the baseline regression model and the mechanism analysis model, and explains the variables and data sources. Sect. "Analysis on the trend of pollutant emissions from listed agricultural companies in China" analyzes the trends in pollutant emissions, including both air and water pollutants, from listed agricultural companies in China. Sect. "Empirical results" reports the estimation results of the baseline and mechanism models and provides relevant analysis. Sect. "Conclusion and policy recommendations" summarizes the main findings, offers policy suggestions, and outlines the study's limitations and directions for future research.

2. Literature review

This paper investigates the nonlinear effects of AI on pollutant emissions in agriculture and explores the underlying mechanisms through which AI influences agricultural pollution. Accordingly, the upcoming literature review is organized around two main themes: artificial intelligence and pollutant emissions and pollutant emissions in agriculture.

2.1 Artificial intelligence and pollutant emissions

AI, as a new generation of general-purpose technology, is profoundly reshaping the way economies operate. As a double-edged sword, AI exhibits a dual effect on pollutant emissions, with both emission-reducing and emission-increasing potentials. Existing studies primarily examine the emission-reducing role of AI from three perspectives: optimizing input structures, enhancing resource allocation efficiency, and fostering green innovation.

(1) AI contributes to the reduction of pollutant emissions by optimizing the structure of factor inputs within enterprises (Cheng et al. 2024). AI-driven smart systems can replace inefficient manual operations, reduce costs, and support investment in cleaner technologies, thereby lowering emission intensity (Zhu et al. 2023; Shang et al. 2024).

(2) AI enhances firms' internal resource allocation efficiency. Algorithmic optimization, real-time monitoring, and data analytics improve the scheduling of materials and energy, reduce redundant inputs, and enhance process efficiency (Usman et al. 2024). This ultimately reduces energy consumption and emissions (Shen and Zhang 2023; Cheng et al. 2024).

(3) AI provides critical support for green technological innovation in enterprises. AI complements skilled labor in green R&D, increases green patenting efficiency, accelerates the development of clean technologies, and improves the diffusion and matching efficiency of green innovations, thus enhancing their spillover effects (Wang et al. 2024; Liu et al. 2025; Wang et al. 2025).

However, some studies argue that AI may also lead to increased pollutant emissions under certain conditions. For instance, Xu et al. (2025) suggest that while AI improves firm productivity and alleviates financial constraints, it may also drive the expansion of production scale, ultimately resulting in higher pollutant emissions. In addition, some studies suggest that when AI technologies are immature or firms face adoption barriers, a mismatch between AI systems and organizational structures may arise, weakening their expected environmental benefits (Lee and Yan 2024; Parra-López et al. 2025).

These conflicting findings regarding AI's environmental impact echo a broader insight from the literature on environmental policy. Beyond technological factors, the literature on environmental policy underscores that the ultimate impact of external interventions—be it regulation or technology—is contingent upon the micro-level transmission mechanisms they activate. For instance, environmental regulations can successfully promote corporate green innovation by reshaping managerial cognition (Zhang et al. 2025), yet they may also backfire by imposing prohibitive compliance costs that crowd out efficiency investments, particularly in certain types of firms (Lei and Kocoglu 2025). This suggests that the net effect of AI on emissions is not predetermined but hinges on whether it primarily triggers efficiency-enhancing and innovation-oriented pathways or conversely leads to cost burdens and maladaptive responses.

2.2 Pollutant emissions in agriculture

Agricultural pollutant emissions exhibit significant non-point source characteristics, such as nutrient runoff from fertilizers and pesticides, livestock waste discharge, and irrigation-related water pollution (Hou et al. 2024; Li and Lei 2025). These emissions are spatially diffuse, temporally variable, and influenced by climatic, hydrological, and soil conditions, making conventional monitoring methods less effective (Kuttippurath et al. 2024; He et al. 2025). As a result, conventional monitoring methods—primarily based on fixed-site measurements and manual surveys—face substantial limitations in identifying pollution sources and tracking their origins in agricultural contexts.

AI offers a novel pathway to address the challenges associated with non-point source pollution in agriculture. Integrated with remote sensing, drones, environmental sensors, and image recognition, AI enables real-time and precise monitoring of nutrient runoff, livestock discharge, and water eutrophication (Usigbe et al. 2024; Ali et al. 2024). Furthermore, embedding AI into precision agriculture—such as intelligent irrigation and variable-rate fertilization—reduces excessive agrochemical use by enabling demand-based input application (Oliveira and Silva 2023; Ghazal et al. 2024; Wang et al. 2025; Khan et al. 2025).

On a broader level, AI influences agricultural pollutant emissions by enhancing operational efficiency and promoting the adoption of green technologies. For instance, AI improves agricultural operations through crop variety optimization, production process refinement, precision resource allocation, and automated task scheduling (Sheikh et al. 2024; Usigbe et al. 2024; Pandey and Mishra 2024). These advancements contribute to more efficient agricultural practices, which in turn affect emission levels. Additionally, AI facilitates green technology adoption, such as recommending eco-friendly inputs and guiding ecological farming models, thereby enabling more effective control of agricultural pollution (Lin et al. 2024).

The mechanisms through which external shocks influence environmental performance extend beyond the agricultural sector, offering valuable comparative insights. Research on extreme climate events reveals that firms' resilience is shaped by strategic investments in green innovation and environmental governance, which can offset physical damages (Lei 2025). Similarly, studies on agricultural credit subsidies demonstrate how financial interventions reduce carbon intensity by facilitating both technological adoption and, notably, agricultural scale expansion (Zhang et al. 2023). This latter point resonates with the potential "scale effect" of AI, suggesting that the interplay between technological advancement and production scaling is a critical, yet underexplored, mechanism determining the environmental outcomes in agriculture.

2.3 Literature gaps

In summary, while the existing literature provides valuable insights, several important research gaps remain. First, although prior studies acknowledge that AI may simultaneously exert both emission-reducing and emission-increasing effects, most theoretical and empirical analyses focus on the industrial sector. Systematic investigations into the mechanisms through which AI affects pollutant emissions in the agricultural sector are still lacking, and empirical evidence remains scarce. Moreover, although classic environmental economics theories—such as the Environmental Kuznets Curve (EKC) (Grossman and Krueger 1991; Kong et al. 2025) and the rebound effect (Qian et al. 2025)—highlight the nonlinear environmental impacts of technological progress, they have rarely been applied to explain the stage-specific pollution effects of AI in agriculture. Second, AI applications in agriculture are widely regarded as crucial tools for promoting green transformation and pollution reduction, with existing studies affirming their roles in enhancing operational efficiency and technological innovation. However, potential unintended consequences—such as scale expansion effects and diminishing marginal returns to green innovation—have not been thoroughly examined in the agricultural context. Therefore, this study uses data from Chinese listed agricultural firms to explore the nonlinear effects of AI on agricultural pollutant emissions and uncover the underlying transmission mechanisms.

3. Mechanism analysis and research hypotheses

3.1 Direct effect of artificial intelligence on pollutant emissions

The rapid development of AI profoundly transforms agricultural production and management (Oliveira and Silva 2023; Sheikh et al. 2024; Wang et al. 2025). AI enhances agricultural productivity by promoting precision agriculture. For example, in the pre-production stage, AI analyzes soil and climate characteristics through algorithms to plan optimal cropping schemes (Aghababaei et al. 2025). During the production stage, AI enables precision weeding and fertilization through image recognition and data analysis (Khan et al. 2025). In addition, AI-driven models such as random forests and neural networks predict rainfall events and optimize irrigation strategies, thereby improving water use efficiency (Pandey and Mishra 2024; Sperandio et al. 2025). While these practices reduce the excessive use of fertilizers and pesticides to some extent, they also increase agricultural productivity, which in turn leads to production scale expansion. This expansion effect results in higher pollutant emissions and intensifies environmental risks (Zhu et al. 2023). Therefore, although AI improves agricultural productivity, it also increases the intensity of agricultural pollutant emissions through the scale expansion effect.

However, as a general-purpose technology, AI faces multiple constraints during its diffusion process—particularly in the early stages—such as limitations in funding, technology, and human resources. First, resource constraints increase the risk of system failures during the implementation of AI (Ghazal et al. 2024). Second, the lack of standardized data protocols in agriculture, along with the presence of bias in some machine learning algorithms, leads to deviations in AI-generated predictions (Yang et al. 2024). Third, the high variability of agricultural production environments and the limited skills of agricultural workers reduce the adaptability of AI technologies (Parra-López et al. 2025). As a result, in the initial phase of AI adoption, these internal and external constraints hinder its practical effectiveness in agricultural systems, lowering both production efficiency and output. Consequently, pollutant emissions from agricultural activities decrease.

Taken together, the impact of AI on agricultural pollutant emissions exhibits a stage-specific pattern. In the early phase of AI application, internal and external constraints limit the technology's effectiveness in enhancing agricultural productivity and scale. As agricultural output declines, pollutant emissions are reduced. As AI adoption deepens, these barriers are gradually alleviated, and the adaptability of the technology improves. At this stage, AI begins to generate productivity effects in agricultural activities, which further lead to scale expansion and increased pollutant emissions.

It is noteworthy that this stage-specific impact is consistent with established environmental economics theories. In the early stage, AI adoption is constrained by limited resources and technical capacity, which suppresses agricultural output and reduces emissions—mirroring the early-phase decline in pollution emphasized in the EKC (Grossman and Krueger 1991; Kong et al. 2025). As AI-induced efficiency gains gradually materialize, expanded production leads to higher pollutant emissions, aligning with the rebound effect, which highlights that efficiency improvements may induce increased resource use and environmental pressure (Qian et al. 2025). Therefore, the nonlinear influence of AI on agricultural pollution reflects the typical patterns described by both the EKC framework and rebound effect mechanisms. Based on this reasoning, we propose Hypothesis 1.

Hypothesis 1 Artificial intelligence exerts a stage-specific impact on agricultural pollutant emissions, initially suppressing and later promoting them.

3.2 Transmission mechanism of artificial intelligence to pollutant emissions

The operational efficiency of agricultural enterprises influences pollutant emissions by shaping agricultural production activities. When operational efficiency improves, the resulting increase in unit output tends to boost total agricultural production (Kumar et al. 2024). This expansion leads to greater use of agricultural inputs such as fertilizers, pesticides, and machinery, thereby intensifying environmental pollution (Aziz and Chowdhury 2023). In contrast, when operational efficiency declines, reduced production intensity lowers the level of agricultural pollutant emissions.

Moreover, AI exerts a dual effect on the operational efficiency of agricultural enterprises. On one hand, in the early stages of AI diffusion and application, deficiencies such as limited data accuracy and system instability hinder performance (Jin and Han 2024). These limitations pose challenges for enterprises in adapting to new technologies. On the other hand, agriculture is a non–technology-intensive sector with a large share of low-skilled labor (Menéndez González et al. 2023). Due to path dependence and cognitive burdens, low-skilled workers generally exhibit low willingness to adopt new technologies and face higher learning costs (Clay et al. 2024). Therefore, constrained by limited technological adaptability and learning barriers among low-skilled workers, AI adoption in the early stages tends to hinder rather than enhance operational efficiency. This mismatch between AI systems and firm's capacity to absorb new technologies reduces operational efficiency. Consequently, the resulting scale contraction effect leads to lower levels of agricultural pollutant emissions.

As AI adoption deepens, intelligent technologies drive continuous transformation in agricultural production activities (Usigbe et al. 2024). This results in an increase in the technological adaptability of agricultural enterprises. At this point, with the deployment of AI systems, the operational efficiency of agricultural enterprises improves (Balcıoğlu et al. 2024; Pandey and Mishra 2024). The improvement in operational efficiency drives the expansion of production scale, which, in turn, increases agricultural pollutant emissions.

Thus, AI affects pollutant emissions by influencing the operational efficiency of agricultural enterprises. In the early stages of AI application, due to the limited learning capacity of unskilled labor and the low adaptability to new technologies, the operational efficiency of agricultural enterprises decreases, leading to a reduction in pollutant emissions. In the later stages of AI implementation, as firms' technological adaptability improves, their operational efficiency increases, which in turn drives the expansion of agricultural production activities, resulting in increased pollutant emissions. Based on this, we propose Hypothesis 2.

Hypothesis 2 Artificial intelligence initially reduces, then increases agricultural firms' operational efficiency, thereby exerting a suppressive-then-promoting effect on agricultural pollutant emissions.

Green innovation refers to the use of green materials and the design of ecological products to achieve energy conservation and reduction of pollutant emissions (Lin et al. 2024; Li et al. 2025). According to this definition, agricultural enterprises can effectively reduce pollutant emissions through the implementation of green innovation.

AI is considered a significant factor influencing corporate green innovation. First, according to innovation diffusion theory, the application of AI technology increases the demand for skilled labor, prompting enterprises to increase investment in research and development (Wang et al. 2024; Liu et al. 2025). Second, AI technology accelerates the dissemination of green knowledge and reduces the failure probability of green innovation processes through data mining and algorithm optimization (Luo and Feng 2024; Zhang 2024). Given that high-skilled labor, such as R&D personnel, has stronger learning capabilities, AI technology in its early stages of application can enhance green technological innovation capability of agricultural enterprises by complementing skills and reallocating resources. This leads to a reduction in pollutant emissions from agricultural enterprises.

However, as enterprises increasingly leverage AI, they may gradually shift internal resources and attention away from green innovation toward other operational priorities. When attention and resources are redirected, green innovation efforts tend to decline (Yang et al. 2024). Consequently, in the later stages of AI application, the reallocation of internal resources and managerial focus reduces the innovation capacity of agricultural enterprises, which in turn leads to increased pollutant emissions. Based on this reasoning, we propose Hypothesis 3.

Hypothesis 3 Artificial intelligence first enhances and then reduces the green innovation capability of agricultural enterprises, thereby exerting a stage-based effect on agricultural pollutant emissions—initially inhibiting them and subsequently promoting them.

To synthesize the dual-path mechanisms described above, Fig. 1 presents the conceptual framework that delineates how AI influences agricultural pollutant emissions through the nonlinear channels of operational efficiency and green innovation.

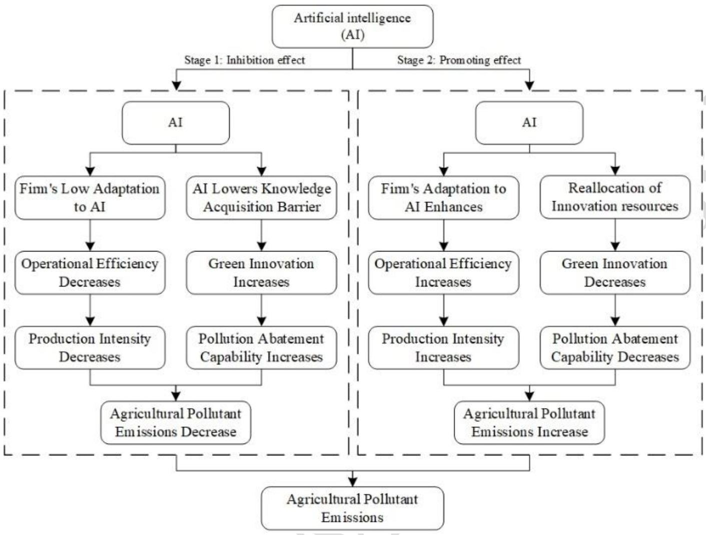


Figure 1. Conceptual framework of AI's nonlinear effects on agricultural pollutant emissions

4. Research design

4.1 Model construction

Based on the theoretical analysis above, AI exhibits a nonlinear effect on pollutant emissions of agricultural enterprises. Following the approach of Miller (2025), we construct a semi-parametric additive model as shown in Equation (1) for empirical analysis. The model effectively captures nonlinear relationships, enhances estimation efficiency, and alleviates dimensionality issues. It also detects potential threshold effects in AI's impact on emissions, offering nuanced insights into stage-specific mechanisms and supporting evidence-based, targeted policy formulation for sustainable agricultural transformation.

$$Pollu_{it} = g(AI_{it}) + \beta_1 Fixed_{it} + \beta_2 TMTPay_{it} + \beta_3 Size_{it} + \beta_4 Lev_{it} + \beta_5 Inst_{it} + \beta_0 + \alpha_i + \varepsilon_{it} \quad (1)$$

In Equation (1), i denotes the individual firm, and t represents the time period. $Pollu_{it}$ is the dependent variable, indicating the level of pollutant emissions of firm i in period t. AI_{it} is the core explanatory variable, measuring the degree of AI adoption in firm i at time t. $Fixed_{it}$, $TMTPay_{it}$, $Size_{it}$, Lev_{it}, $Inst_{it}$ are the selected control variables, whose selection rationale and measurement are elaborated in Section 4.3.3. β_0 is the intercept term. α_i captures the individual fixed effects, and ε_{it}

represents the random error term.

4.2 Mechanism test model

To examine the mechanism through which AI affects pollutant emissions in agricultural enterprises, we follow the framework of Yang et al. (2024) and construct a regression model as shown in Equation (2).

$$M_{it} = g(AI_{it}) + \beta_1 Fixed_{it} + \beta_2 TMTPay_{it} + \beta_3 Size_{it} + \beta_4 Lev_{it} + \beta_5 Inst_{it} + \beta_0 + \alpha_i + \varepsilon_{it} \quad (2)$$

In Equation (2), M_{it} represents the mediating variables, specifically operational efficiency ($OperEffic$) and green innovation capability ($GreenInno$). The definitions of the other variables are consistent with those in Equation (1).

4.3 Variables

4.3.1 Dependent variable

Enterprise pollutant emissions ($Pollu$) include water pollutant emissions ($Water\_Pollu$) and air pollutant emissions (Air_Pollu). According to Wang et al. (2023), major agricultural water pollutants include chemical oxygen demand (COD), ammonia nitrogen ($NH3 - N$), total nitrogen (TN), and total phosphorus (TP). Based on the analyses of Kuttippurath et al. (2024) and Mousavi et al. (2023), major agricultural air pollutants include sulfur dioxide ($SO2$), nitrogen oxides (NO), and smoke.

To measure enterprise pollutant emissions ($Pollu$), we first collect data on emissions of each water and air pollutant from agricultural enterprises. Second, we refer to the *Administrative Measures for the Collection Standards of Pollution Discharge Fees* to identify the pollution equivalent value for each pollutant. Then, all emissions are converted into standardized pollution equivalents, summed, and transformed by taking the natural logarithm of the total plus one. The resulting value reflects the overall level of pollutant emissions from agricultural enterprises.

4.3.2 Independent variable

According to Choi (2024), software and hardware are essential components of digital systems. Following the approach of Song et al. (2024), this study focuses on enterprise investments in software and hardware related to AI. We measure the level of AI in agricultural enterprises by the intensity of their AI-related software and hardware investments. Specifically, we calculate the sum of AI software and hardware investment amounts, take the natural logarithm of this total, and use the result as an indicator of the enterprise's AI level (AI).

4.3.3 Control variables

To control for potential omitted variable bias, drawing on relevant studies (Cheng et al. 2024; Xu et al. 2025), we select the following variables as controls to suit the context of this study: (1) the share of fixed assets ($Fixed$), measured by the ratio of fixed assets to total assets. A higher proportion indicates a more capital-intensive firm structure, which, particularly in agriculture, reflects greater reliance on machinery and infrastructure associated with increased resource consumption and emissions. Therefore, a positive association with pollutant emissions is expected (Xu et al. 2025). (2) top management team compensation ($TMTPay$), measured by the natural logarithm of the compensation of the top three executives. As executive compensation is often linked to short-term performance targets, it may incentivize profit-driven strategies that neglect environmental externalities, potentially leading to higher emissions (Kong et al. 2024). (3) firm size ($Size$), measured by the natural logarithm of total assets at the end of the year. Larger agricultural firms typically operate on a greater scale and consume more energy, resulting in higher levels of pollution (Xu et al. 2025). (4) leverage (Lev), measured by the ratio of total liabilities to total assets at year-end. Firms with higher leverage are subject to tighter financial constraints, reducing their operational resilience (Foulon and Marsat 2023). As a result, they may adopt more conservative strategies, such as downsizing or investing in cleaner technologies, to mitigate environmental and regulatory risks. Hence, leverage is expected to be negatively associated with pollutant emissions. (5) institutional ownership ($Inst$), measured by the proportion of shares held by institutional investors relative to total shares outstanding. Firms with higher institutional ownership are subject to stronger governance pressure and collaborative incentives from common investors, making them more likely to take proactive environmental actions and thus exhibit lower levels of pollutant emissions (Qiang et al. 2025).

4.3.4 Mechanism variables

This study also incorporates two mechanism variables: operational efficiency ($OperEffic$) and green innovation capability ($GreenInno$).

Inventory turnover reflects the enterprise's management capacity in terms of production, logistics, capital flow, and market responsiveness. Therefore, we use inventory turnover as a proxy for operational efficiency.

In addition, drawing on the methodologies of Xiang and Geng (2024) and Wang et al. (2025), we construct a green innovation capability indicator based on the number of green invention patents and green utility model patents. Specifically, we sum the number of independently filed green invention patents and green utility model patents by each agricultural enterprise in a given year, add one to avoid logarithmic transformation of zero, and take the natural logarithm. This value serves as a proxy for the firm's green innovation capability.

4.4 Sample selection and data source

The dependent variable of this study, firm pollutant emissions, is based on raw data obtained from corporate annual reports, government sustainability reports, and disclosures by environmental protection authorities. Python software is used to batch-scrape these reports and extract the required pollutant emission data. The original data for the core explanatory variable, control variables, and mechanism variables are obtained from the CSMAR Database and the Chinese Patent Database. After matching the samples and variables, we select listed firms in the agricultural sector from 2010 to 2022 as the analysis sample.

This sample period is chosen based on a combination of policy relevance and data availability. On the one hand, 2010 marks a significant starting point in China's agricultural informatization and intelligent transformation. In that year, five key government ministries—including the Ministry of Industry and Information Technology, the Ministry of Agriculture, and the Ministry of Science and Technology, among others—jointly issued the *Action Plan for Agricultural and Rural Informatization (2010–2012)*. This initiative officially launched the country's digital agriculture agenda and laid the groundwork for the application of AI technologies in the agricultural sector. On the other hand, 2022 represents the latest year for which complete and reliable data are available for all key variables. Due to the lag in environmental and financial disclosures by listed companies, some pollutant emission data for agricultural firms remain incomplete or of inconsistent quality beyond 2022. Thus, setting 2022 as the endpoint of the sample period ensures data integrity and analytical robustness. In sum, the 2010–2022 period is both policy-relevant and empirically justified for investigating the relationship between AI and agricultural pollutant emissions.

Table 1. Descriptive statistics of main variables

Variable	Observations	Mean	Standard deviation	Min	Max
$Ln\,TotalPollu$	189	0.143	0.005	0.132	0.152
AI	189	11.946	5.601	0.000	18.563
$Fixed$	189	0.214	0.128	0.000	0.643
$TMTPay$	188	13.934	0.811	9.68	16.101
$Size$	189	21.756	1.047	18.946	23.829
Lev	189	0.421	0.218	0.030	0.937
$Inst$	189	0.435	0.209	0.012	0.838

The final unbalanced panel includes 22 listed agricultural firms, yielding a total of 189 firm-year observations. Descriptive statistics for the main variables used in the baseline analysis are reported in Table 1. Among these, 19 firms are identified as having adopted AI in at least one year during the sample period. To further clarify the timeframe during which AI has been applied by agricultural firms, we present in Fig. 2 the annual number of companies reporting non-zero AI investment from 2010 to 2022. In our study, firm-level AI application is proxied by annual AI-related investment, as recorded in the CSMAR database. As shown in Fig. 2, agricultural firms began investing in AI as early as 2010, with 11 firms reporting such investment in that year. Throughout the sample period, the number of AI-investing firms per year ranged from 10 to 15, indicating a steady—albeit uneven—uptake of AI technologies in the sector. This pattern offers a concrete temporal basis for analyzing the environmental effects of AI adoption.

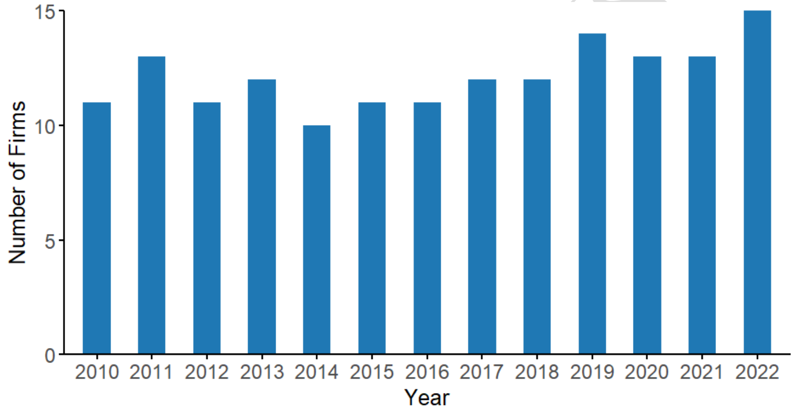


Figure 2. Annual number of agricultural firms investing in AI during 2010 to 2022

Note: A firm is counted in a given year only if it has non-zero AI investment in that year. Hence, although 19 firms adopted AI at least once during the sample period, the number of adopting firms varied year by year.

In light of this, we retain firm-year observations in which AI investment was zero, including years prior to the initial AI adoption by each firm and firms that never adopted AI during the entire sample period. This approach is methodologically justified for several reasons. First, including pre-AI years enables a more comprehensive within-firm comparison of emission outcomes before and after AI adoption. Second, maintaining non-AI firms in the sample helps establish a valid counterfactual, strengthening the identification of AI's effects. Lastly, given that 2010 marked the launch of China's national agricultural digitalization strategy, retaining data from this year onward is consistent with the broader policy context and allows us to capture the early diffusion of AI technologies in agriculture.

5. Analysis on the trend of pollutant emissions from listed agricultural companies in China

5.1 Analysis on the trend of water pollutant discharge

We aggregate the water pollutant emissions ($Water\_Pollu$) of all listed agricultural firms in China from 2010 to 2022. Specifically, we sum the emissions of chemical oxygen demand (COD), ammonia nitrogen ($NH3-N$), total nitrogen (TN), and total phosphorus (TP) for all listed agricultural firms. The trends of each type of water pollutant are then plotted, as shown in Fig. 3.

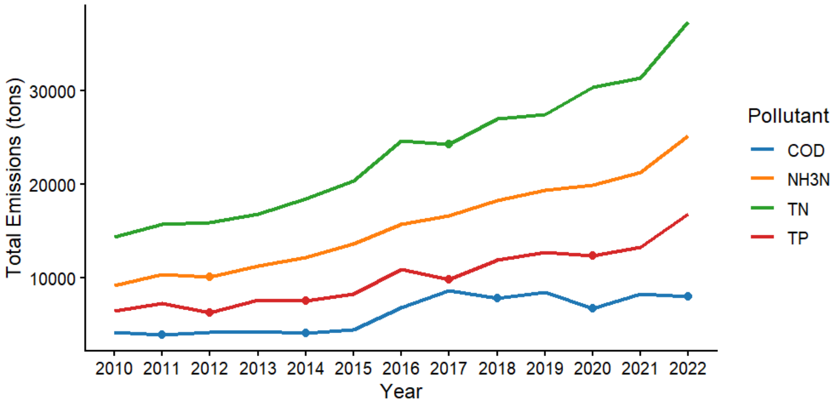


Figure 3. Trends in the total water pollutant emissions from listed agricultural companies in China

Note: Marked points indicate years in which the emissions of the corresponding pollutant decreased relative to the previous year.

According to Fig. 3, the total water pollutant emissions of listed agricultural firms in China show an overall upward trend from 2010 to 2022. Specifically, this trend can be divided into four distinct phases.

The first phase (from 2010 to 2014): During this period, the total emissions of chemical oxygen demand (COD), ammonia nitrogen ($NH3-N$), total nitrogen (TN), and total phosphorus (TP) from China's listed agricultural firms increase at a relatively moderate pace. This phase coincides with the initial stage of the introduction and refinement of agricultural environmental policies in China, during which policy enforcement and infrastructure development still lag behind. In addition, the degree of agricultural scale expansion remains relatively low, and the intensity of fertilization and livestock production per unit of land tends to stabilize, resulting in a controllable rate of increase in total emissions.

The second phase (from 2014 to 2018): The emissions of COD, $NH3-N$, TN, and TP rise sharply. This trend is closely related to the accelerated expansion and modernization of the agricultural sector. At the same time, with the gradual improvement of the environmental information disclosure system, the coverage and transparency of environmental data disclosure by listed firms also improve, possibly broadening the statistical scope of emission data and thus contributing to a noticeable increase in reported emissions.

The third phase (from 2018 to 2020): The growth rate of all water pollutant emissions slows down. This change is associated with the strengthening of environmental governance policies at the national level. The implementation of relevant agricultural environmental regulations strengthens supervision intensity. Meanwhile, green production practices, such as soil testing and formulated fertilization, organic fertilizer substitution, and integrated crop-livestock systems, gain increasing attention. Some highly polluting livestock projects are also restricted or shut down, which effectively alleviates the water pollution burden.

The fourth phase (from 2020 to 2022): The emissions of $NH3-N$, TN, and TP increase rapidly, while COD emissions decrease. This divergence may be explained by two main factors. First, the expansion of agricultural production and the improper application of certain green technologies (such as the excessive use of nitrogen fertilizers) lead to increased emissions of nitrogen and phosphorus pollutants. Second, as COD reflects organic matter pollution, its reduction may be attributed to improvements in wastewater treatment capacity or enhanced recycling of livestock waste. In addition, more mature standards and regulatory measures for COD emissions at the policy level also play a role in curbing such emissions.

5.2 Analysis of changing trends in air pollutant emissions

We also aggregate the air pollutant emissions (Air_Pollu) for all listed agricultural firms in China. Specifically, we sum the emissions of sulfur dioxide ($SO2$), nitrogen oxides (NO), and smoke for all listed agricultural firms. We then plot the trends for each type of air pollutant, as shown in Fig. 4.

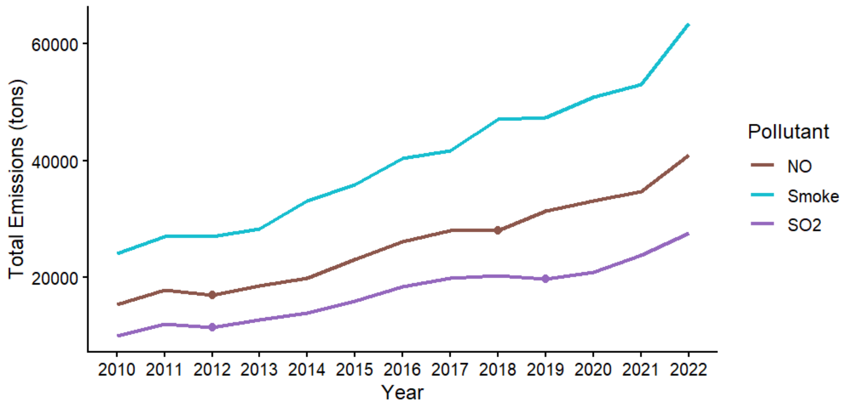


Figure 4. Trends in total air pollutant emissions from listed agricultural companies in China

Note: Marked points indicate years in which the emissions of the corresponding pollutant decreased relative to the previous year.

According to Fig. 4, total air pollutant emissions from listed agricultural firms in China show an overall upward trend from 2010 to 2022. Specifically, the changes can be divided into four distinct stages.

The first stage covers the years 2010 to 2013. During this period, the combined emissions of sulfur dioxide ($SO2$), nitrogen oxides (NO) and smoke from listed agricultural firms exhibit a slow upward trend. This suggests that China's agricultural modernization remains at an early stage, with relatively limited mechanization and scale, resulting in relatively moderate growth in air pollution emissions.

The second stage spans from 2013 to 2016. During this period, the total emissions of $SO2$, NO and smoke continue to rise, and the growth rate significantly accelerates. This trend is closely related to the rapid advancement of agricultural modernization and the continuous expansion of agricultural production in China.

The third stage covers the years 2016 to 2020. In this period, the growth of $SO2$ emissions slows significantly and even begins to decline, while the growth rate of NO emissions also decreases. However, smoke emissions continue the rapid upward trend observed in the previous stage. This divergence may be closely related to environmental protection policies and the development of green technologies. Pollution control initiatives promote the substitution of coal, the application of clean energy, and the widespread adoption of desulfurization and denitrification technologies, thereby curbing the growth of $SO2$ and NO emissions. In contrast, smoke control remains technically challenging, especially in agriculture, such as straw burning, open-air processing, and waste disposal from livestock. The slow improvement in technology and difficulties in enforcement contribute to the continued rise in smoke emissions.

The fourth stage spans from 2020 to 2022. In this stage, the total emissions of all three air pollutants increase sharply again, with the fastest growth observed across all periods. This may be due to, first, the rapid post-pandemic recovery and expansion of agricultural production, which substantially raises energy demand and the use of agricultural machinery. Second, the gradual improvement in emissions disclosure systems leads to more complete enterprise reporting, which may broaden the statistical coverage and result in an apparent surge in total emissions.

6. Empirical results

6.1 Baseline regression

The estimation results of the baseline model are shown in Column (1) of Table 2. In addition, the marginal effect diagram of the core independent variable AI on corporate pollutant emissions is shown in Fig. 5.

Table 2. Estimation results of semiparametric additive model

Variable	(1) Baseline regression results	(2) Robustness test I	(3) Robustness test II
AI	See Fig. 5**	See Fig. 6***	See Fig. 7**
$(Intercept)$	0.044**	0.041*	0.057***
	(0.020)	(0.023)	(0.021)
$Fixed$	0.001	0.000	0.003
	(0.005)	(0.006)	(0.006)
$TMTPay$	0.004***	0.004***	0.004***
	(0.001)	(0.001)	(0.001)
$Size$	0.002**	0.002**	0.002**
	(0.001)	(0.001)	(0.001)
Lev	-0.008***	-0.009***	-0.008***
	(0.003)	(0.003)	(0.003)
$Inst$	-0.021***	-0.020***	-0.021***
	(0.003)	(0.004)	(0.004)

Note: *, **, *** indicate significant at the 10%, 5%, and 1% significance levels, respectively. The standard error is in brackets.

According to Fig. 5, the marginal effect of AI investment intensity on pollutant emissions in agricultural firms first decreases and then increases. The value of the marginal effect is initially negative and later becomes positive. This indicates that the use of AI in agricultural firms follows a pattern of initially reducing and then increasing pollutant emissions, which supports Hypothesis 1 of this study. The impact of AI on agricultural pollution exhibits a two-stage characteristic. At low levels of AI adoption, resource constraints reduce production efficiency and output. As a result, pollutant emissions decline. At high levels of AI adoption, AI enables firms to expand production scale. This expansion leads to an increase in agricultural pollutant emissions.

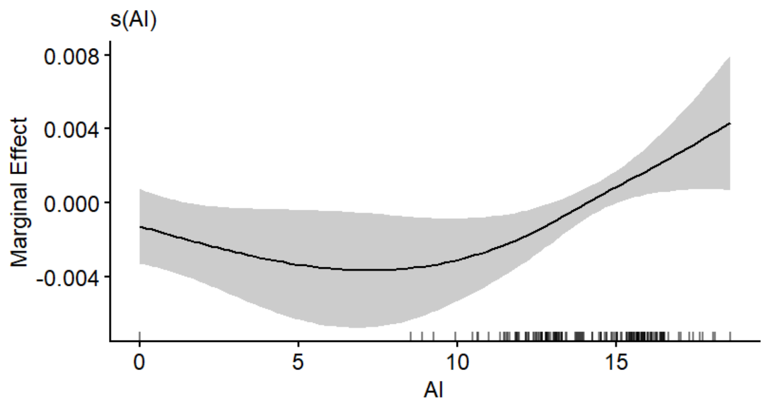


Figure 5. The marginal effect of AI in agricultural enterprises on pollutant emissions

Specifically, when the logarithm of AI investment in agricultural firms is less than approximately 7, AI has a suppressive effect on pollutant emissions, and this effect becomes increasingly stronger. This suggests that at this stage, agricultural firms face significant internal and external resource constraints. Issues such as failure risks and poor technological compatibility are prominent, limiting productivity improvements and scale expansion. As firms reduce production scale, pollutant emissions decline more rapidly.

When the logarithm of AI investment ranges between 7 and 14, AI still reduces pollutant emissions, but the suppressive effect gradually weakens. This indicates that firms begin to seek ways to overcome resource constraints and reverse the decline in productivity. The problems of failure risk and technological mismatch become less severe. The decline in production scale and output slows, leading to a smaller reduction in pollutant emissions.

However, when the logarithm of AI investment exceeds 14, AI begins to promote pollutant emissions, and this effect intensifies. This implies that firms have overcome resource limitations, and issues related to failure risk and compatibility are effectively resolved. Agricultural firms can leverage AI to enhance productivity and expand production scale. As production and operational activities increase, the intensity of pollutant emissions also rises continuously.

6.2 Robustness test

To test the robustness of our estimation results, we follow the approaches of Ma et al. (2024) and Ling et al. (2024), and conduct robustness checks using three methods: replacing the explained variable, changing the model estimation method, and adding control variables.

6.2.1 Replace the explained variable

We replace the original dependent variable—total pollutant emissions ($Pollu$)—with water pollutant emissions ($Water\_Pollu$) and air pollutant emissions (Air_Pollu), respectively, to re-estimate the model for robustness testing. At the same time, this approach allows us to analyze the separate effects of AI on firms' water and air pollutant emissions. The robustness test results are shown in Column (2) "Robustness test I" and Column (3) "Robustness test II" of Table 2.

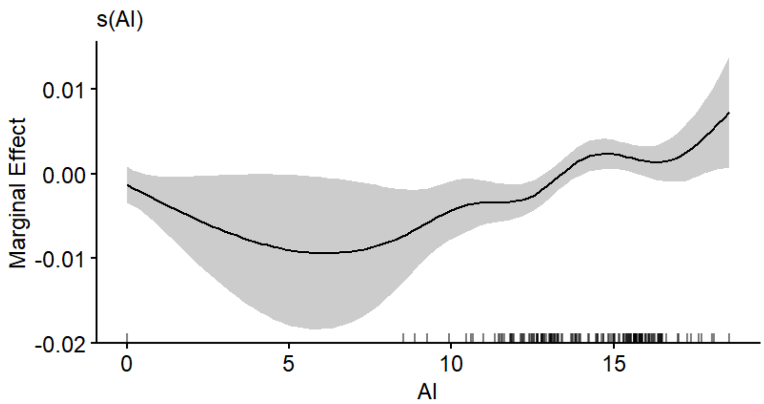


Figure 6. The marginal effect of AI in agricultural enterprises on water pollutant emissions

According to Fig. 6 and Fig. 7, after replacing the dependent variable with water pollutant emissions ($Water\_Pollu$) and air pollutant emissions (Air_Pollu), respectively, the overall marginal effect trend of AI remains unchanged. The marginal effects of AI investment intensity on water and air pollutant emissions both show a trend of first decreasing and then increasing. Moreover, the marginal effects are initially negative and later become positive. This indicates that the use of AI in agricultural enterprises first suppresses and then promotes water and air pollutant emissions, thereby reaffirming Hypothesis 1 of this paper. The impact of AI on agricultural pollution exhibits a stage-specific pattern, characterized by initial suppression followed by promotion. In addition, the directions of the control variables' effects remain consistent, with only differences in magnitude and statistical significance. This confirms the robustness of the estimation results.

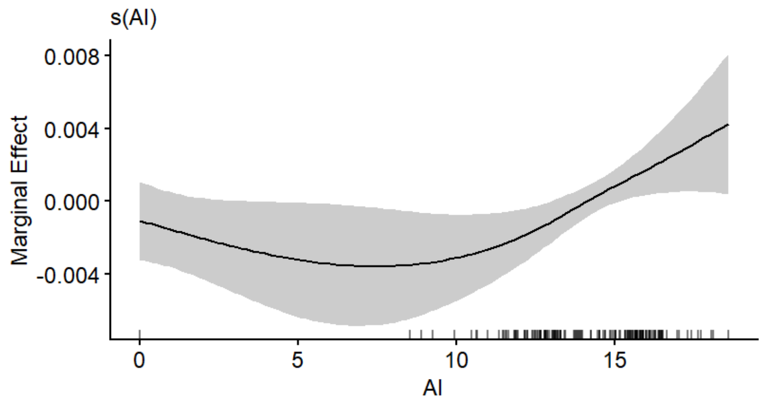


Figure 7. The marginal effect of AI in agricultural enterprises on air pollutant emissions

A comparison of Fig. 5, Fig. 6, and Fig. 7 reveals that the impact pattern of AI investment on total pollutant emissions closely mirrors that on air pollutant emissions, while the effect on water pollutants exhibits slight deviations. Notably, when the logarithm of AI investment exceeds 14, the intensity of water pollutant emissions exhibits a fluctuating upward trend—rising, then falling, and rising again. This indicates that in the initial phase of production expansion, agricultural enterprises primarily contribute to the sharp increase in air pollutant emissions.

6.2.2 Changing the model estimation method

When estimating the semi-parametric additive model, we change the type and degrees of freedom of the smoothing function compared with the baseline model, and re-estimate the model to conduct robustness checks. Specifically, we replace the default "Thin Plate Regression Spline" with the "Cubic Regression Spline" and the "Natural Cubic Spline," respectively. At the same time, we modify the degrees of freedom. The estimation results are shown in Column (1) “Robustness test III” and Column (2) “Robustness test IV” of Table 3.

Table 3. Robustness test model estimation results

Variable	(1) Robustness test III	(2) Robustness test IV	(3) Robustness test V
AI	See Fig. 8***	See Fig. 9***	See Fig. 10***
$(Intercept)$	0.057***	0.057***	0.034**
	(0.021)	(0.021)	(0.014)
Cap			0.001***
			(0.000)
DER			-0.017**
			(0.007)
EM			0.017**
			(0.007)
BM			-0.010***
			(0.003)
$Fixed$	0.003	0.003	-0.001
	(0.006)	(0.006)	(0.006)
$TMTPay$	0.004***	0.004***	0.004***
	(0.001)	(0.001)	(0.001)
$Size$	0.002**	0.002**	0.002**
	(0.001)	(0.001)	(0.001)
Lev	-0.008***	-0.008***	-0.008**
	(0.003)	(0.003)	(0.004)
$Inst$	-0.021***	-0.021***	-0.022***
	(0.004)	(0.004)	(0.003)

Note: *, **, *** indicate significant at the 10%, 5%, and 1% significance levels, respectively. The standard error is in brackets.

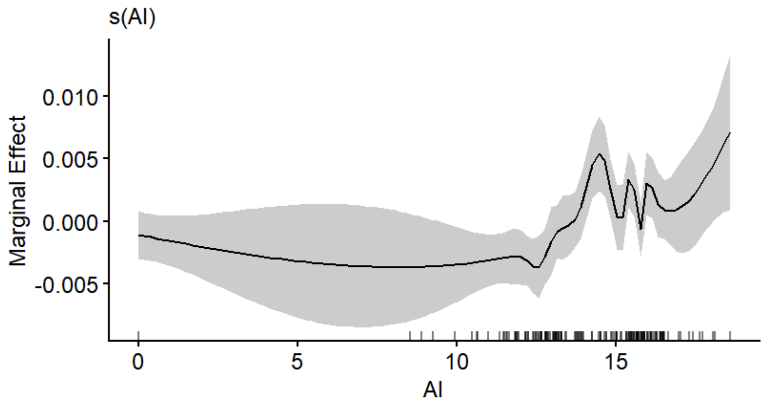


Figure 8. The marginal effect of AI on pollutant emissions after changing the model estimation method

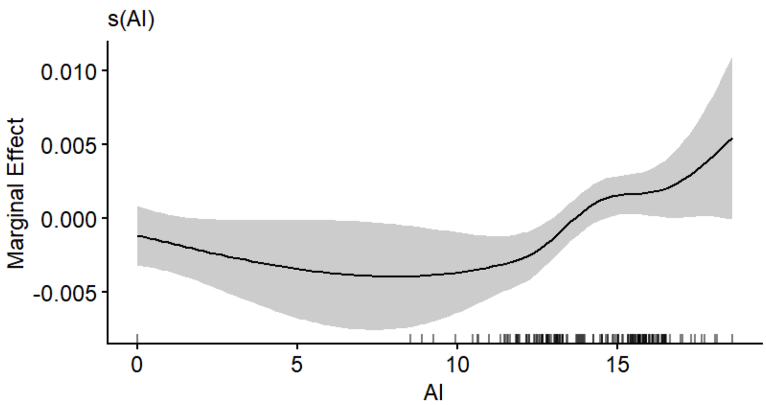


Figure 9. The marginal effect of AI on pollutant emissions after changing the model estimation method

According to Fig. 8 and Fig. 9, after changing the smoothing function and degrees of freedom, the overall trend of the marginal effect of AI on agricultural firms' pollutant emissions remains unchanged, with only differences in the degree of fluctuation. The coefficient directions of the control variables also remain consistent with those in the baseline model. This further confirms the robustness of the estimation results.

6.2.3 Adding control variables

Drawing on the study by Ma et al. (2024), we add additional control variables to the baseline model to account for potential confounding factors and implement stricter controls. We then re-estimate the model to conduct a robustness check.

Specifically, the additional control variables include: capital intensity (Cap), measured by the ratio of total assets to operating revenue; debt-to-equity ratio (DER), measured by the ratio of total liabilities to shareholders' equity at the end of the year; equity multiplier (EM), measured by the ratio of total assets to shareholders' equity at year-end; and book-to-market ratio (BM), measured by the ratio of book value to market value. The estimation results are reported in Column (3) of Table 3 under Robustness test V.

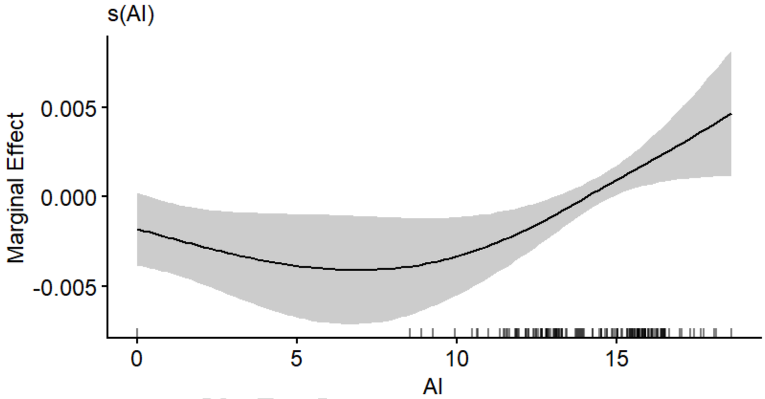


Figure 10. The marginal effect of AI on pollutant emissions after adding control variables

According to Fig. 10, after incorporating additional control variables, the marginal effect of AI on agricultural firms' pollutant emissions remains consistent with the baseline model. Specifically, at a low level of AI usage, it exerts a suppressive effect on pollutant emissions. As the level of AI usage increases, it gradually exhibits a promoting effect on emissions, and this promoting effect continues to intensify. These findings further confirm the robustness of the conclusions in this study.

6.3 Mechanism analysis

Theoretical analysis and empirical results presented earlier show that the level of AI investment in agricultural firms exerts a direct effect on their pollutant emissions, which first suppresses and then promotes emissions. To further explore the underlying mechanism of this effect, we follow the approach of Yang et al. (2024) and estimate the specified Model (2).

6.3.1 Operational efficiency

The estimation results of the mechanism model based on operational efficiency are shown in Column (1) of Table 4.

Table 4. Estimation results of the mechanism test models

Variable	(1) Operational efficiency	(2) Green innovation capabilities
AI	See Fig. 11***	See Fig. 12*
$(Intercept)$	376.180***	-2.267**

	(53.817)	(0.889)
$Fixed$	-56.173***	0.505**
	(13.121)	(0.241)
$TMTPay$	-1.655	0.048*
	(1.484)	(0.027)
$Size$	-16.593***	0.068*
	(2.448)	(0.041)
Lev	11.361*	-0.139
	(6.703)	(0.122)
$Inst$	12.372	0.100
	(8.262)	(0.149)

Note: *, **, *** indicate significant at the 10%, 5%, and 1% significance levels, respectively. The standard error is in brackets.

According to Fig. 11, the marginal effect of AI investment on the operational efficiency of agricultural firms shows a downward-then-upward trend. The value of the marginal effect is initially less than zero and then becomes greater than zero. This indicates that the use of AI by agricultural firms first suppresses and then promotes their operational efficiency, which confirms Hypothesis 2 of this paper. AI affects pollutant emissions intensity by influencing the operational efficiency of agricultural firms. AI investment initially reduces and then enhances operational efficiency, thereby exerting a suppressing-then-promoting effect on agricultural pollutant emissions.

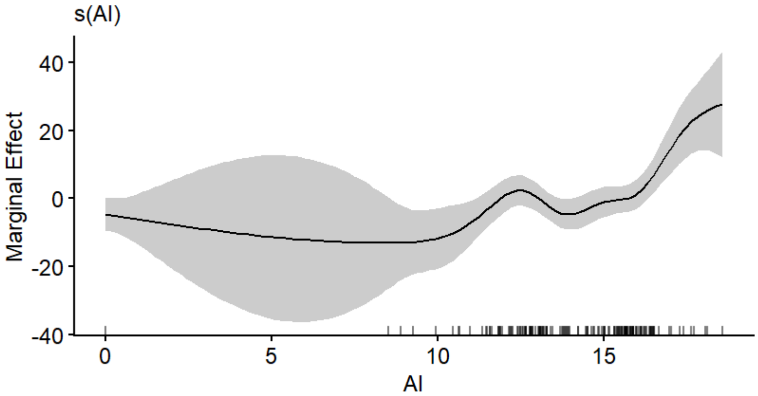


Figure 11. The marginal effect of AI on operational efficiency in agricultural enterprises

Specifically, when the logarithmic value of AI investment by agricultural firms is less than approximately 14, it exerts a suppressing effect on operational efficiency. This suppressing effect shows a trend of first decreasing, then increasing, and finally slightly declining. This suggests that, during this stage, firms are constrained by both limited technological adaptability and learning barriers among unskilled labor, resulting in reduced operational efficiency. This hinders the expansion of production scale and leads to a reduction in pollutant emissions. Meanwhile, when the logarithmic value of AI investment is approximately equal to 10, the decline in operational efficiency becomes controlled, indicating that issues related to technological adaptability and labor learning barriers begin to ease.

When the logarithmic value of AI investment exceeds approximately 14, it promotes operational efficiency, with the marginal effect exhibiting an accelerating yet fluctuating upward trend. This indicates that, during this stage, technological adaptability improves continuously, and learning barriers for unskilled labor are gradually overcome. As a result, firms become increasingly adaptive, which accelerates improvements in operational efficiency. As operational efficiency rises, the resulting productivity and scale expansion effects lead to a rapid increase in pollutant emissions.

6.3.2 Green innovation capabilities

The estimation results of the mechanism model based on green innovation capabilities are shown in

Column (2) of Table 4.

According to Fig. 12, the marginal effect of AI investment by agricultural firms on their green innovation capability generally follows an inverted U-shaped pattern, first increasing and then decreasing. The marginal effect value first falls below zero, then rises above zero, and eventually drops below zero again. Although in the early stage of AI investment—when the logarithmic value of AI investment is approximately less than 4—the marginal effect is negative, its magnitude becomes less negative over time. Therefore, overall, AI exerts a promoting effect followed by a suppressing effect on agricultural firms' green innovation capability, which supports Hypothesis 3. AI influences pollutant emissions by affecting firms' green innovation capability. Specifically, AI investment intensity first enhances and then reduces green innovation, which in turn first suppresses and later promotes pollutant emissions.

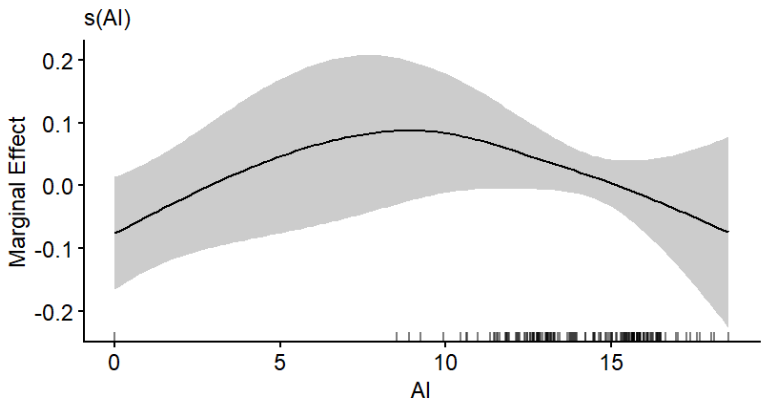


Figure 12. The marginal effect of AI on green innovation capabilities of agricultural enterprises

Specifically, when the logarithmic value of AI investment in agriculture is approximately less than 4, it exerts a suppressing effect on firms' green innovation, although this negative effect gradually weakens. A possible reason for this phenomenon is that in the initial stage of AI adoption, firms require time to allocate appropriate R&D resources. The resulting time-lag effect prevents AI from showing a positive impact on green innovation capability during this stage.

However, when the logarithmic value of agricultural AI investment is approximately greater than 4 but less than 14, it promotes green innovation capability. This suggests that AI can effectively enhance agricultural firms' green technology innovation through complementary effects. At the same time, this promoting effect first strengthens and then weakens, indicating a saturation trend in the enabling effect of AI as investment intensity increases. After reaching a peak, the positive impact on green innovation gradually diminishes.

Finally, when the logarithmic value of agricultural AI investment exceeds 14, it again exerts a suppressing effect on green innovation capability. This implies that as AI investment intensity continues to rise, firms gradually shift their attention and internal resources away from innovation, leading to a decline in green innovation. As a result, pollutant emissions increase. Moreover, the suppressing effect continues to intensify, indicating that the negative impact of resource reallocation and attention diversion on green innovation persists and strengthens over time. This leads to a continuous increase in pollutant emission intensity.

Our empirical findings offer important extensions to the existing body of literature. First, existing studies primarily focus on industrial enterprises to examine the impact of AI applications on pollutant emissions (Shang et al. 2024; Cheng et al. 2024; Xu et al. 2025). In contrast, empirical investigations into the agricultural sector remain relatively limited. This study addresses this gap by using listed agricultural firms in China as the research sample and systematically analyzing the effects of AI on agricultural pollutant emissions. It thus provides valuable empirical evidence to supplement the literature. Moreover, this study finds that AI exerts a two-stage effect on agricultural emissions—initially reducing them and subsequently increasing them—whereas most existing studies in the industrial context report a consistently negative effect of AI on pollution.

Second, Lin et al. (2024) suggest that AI enhances environmental performance in agricultural enterprises by promoting green innovation. Building on this insight, this study further reveals that green innovation capacity is constrained by firms' absorptive limits. As AI adoption advances to later stages, firms may experience a decline in green innovation efficiency due to saturation of absorptive capacity, which in turn leads to a rebound in pollutant emissions. This finding implies the existence of a threshold effect in the environmental benefits of AI.

Finally, some prior studies identify that AI indirectly affects corporate emissions by influencing resource allocation, input structure, and energy efficiency (Shen and Zhang 2023; Zhou et al. 2024; Cheng et al. 2024). Extending this line of inquiry, the present study incorporates the perspective of operational efficiency and finds that AI first improves and then weakens the operational efficiency of agricultural enterprises, resulting in a nonlinear emission pattern characterized by "initial reduction followed by subsequent increase." This mechanism is particularly important because operational efficiency is closely related to production scale. Continuous improvements in efficiency tend to drive production expansion, which may amplify pollutant emissions and weaken the long-term mitigation effects of AI.

In sum, this study not only broadens the application scope of AI's environmental impacts by introducing the agricultural sector but also uncovers nonlinear transmission mechanisms—via green innovation capacity and operational efficiency—that significantly enrich the existing literature both theoretically and empirically.

7. Conclusion and policy recommendations

7.1 Conclusion

This paper analyzes the nonlinear impact path and underlying mechanism of AI on pollutant emissions in agricultural firms. Using listed agricultural companies in China from 2010 to 2022 as the sample, it constructs a semi-parametric additive model to empirically test the specific path through which AI investment intensity affects pollutant emissions. It further explores the internal mechanisms from the perspectives of operational efficiency and green innovation capability. The main conclusions are as follows:

First, AI has a phased impact on pollutant emissions in agricultural firms, showing an initial suppressive effect followed by a promoting effect. At low levels of AI adoption, internal and external resource constraints lead to reductions in production efficiency and scale, resulting in lower pollutant emissions. As AI usage intensifies, the resulting improvements in productivity and scale expansion lead to increased emissions.

Second, the impact path of AI on total pollutant emissions is consistent with its effect on air pollutants, while it differs slightly in the case of water pollutants. Specifically, at higher levels of AI usage, water pollutant intensity shows a fluctuating trend—rising, then falling, and rising again. This suggests that during the early stage of production expansion, AI primarily leads to a rapid increase in air pollutant emissions.

Third, AI influences agricultural pollutant emissions through a nonlinear effect on operational efficiency—first reducing and then enhancing it. In the early stage of AI application, firms face limitations from new technology adaptation and learning barriers among unskilled labor, which reduces operational efficiency and hinders production scale expansion, thereby lowering emissions. As AI adoption deepens, technological adaptation improves, learning barriers diminish, and firm adaptability increases, leading to rapid gains in operational efficiency and, consequently, a sharp rise in pollutant emissions.

Finally, AI affects pollutant emissions by first enhancing and then weakening green innovation capacity in agricultural firms. At low levels of AI use, resource allocation and the complementary effect with skilled labor improve green innovation, reducing emissions. As AI use intensifies, diminishing returns set in, innovation resources are reallocated, and organizational attention shifts—factors that gradually erode green innovation capacity and lead to rising pollutant emissions.

7.2 Policy recommendations

Building upon the empirical findings, this section discusses their broader implications for policy design and managerial practice. The results reveal that AI adoption exerts a nonlinear environmental effect in agricultural enterprises—emissions decline in the early stages but rebound as adoption deepens. This U-pattern is transmitted through two key mechanisms: green innovation capacity and operational efficiency. These dynamics suggest that simple promotion of AI may not guarantee sustainable emission reductions unless paired with supportive policy and managerial responses. Accordingly, the following recommendations are proposed:

First, it is important to improve the AI technology adaptation mechanism to shorten the "low-efficiency adaptation period" during the initial stage of digital transformation in agricultural firms. The research shows that in the early phase of AI application, agricultural firms often face problems such as poor technological compatibility and long learning curves for unskilled labor. These issues reduce operational efficiency and constrain production activities, leading to a temporary decline in pollutant emissions. To prevent such "false reductions" from masking structural problems, the government is advised to strengthen public support for AI applications in agriculture. This includes establishing technical adaptation guidance centers, launching standardized solutions for different sub-industries, and offering skill training and hands-on coaching for grassroots agricultural firms to help them overcome the initial adaptation gap and achieve both technological progress and green development.

Second, a differentiated regulatory mechanism should be introduced to manage the emission rebound associated with large-scale AI adoption. As AI usage increases, productivity improves significantly and industrial expansion accelerates, which leads to a rapid rise in pollutant emissions. To address this risk, pollutant emission intensity should be embedded into capacity-expansion approval, AI-related subsidy qualification, and green credit evaluation. Firms with a severe disconnect between expansion and emission control should be subject to capacity constraints and enhanced environmental supervision to prevent the spread of " high-intelligence but high-emission expansion."

Finally, the positive impact of AI on green innovation should be strengthened to avoid the marginal decline of its long-term enabling effects. The research shows that AI initially promotes green innovation in agricultural firms through resource restructuring and complementarity, thereby effectively curbing emissions. However, as AI adoption deepens, firms may shift their resource allocation to non-green areas, weakening their green innovation capacity. To sustain AI's green-enabling effect, a coordinated policy framework—linking AI adoption with green R&D incentives—should be implemented to guide firms in applying AI to energy saving, cleaner production, and resource recycling. It is recommended to establish special funds, provide green tax incentives, and introduce performance-linked environmental subsidies. Incorporating green technology outcomes into performance evaluation and financing criteria can further strengthen firms' long-term motivation for continuous green innovation.

7.3 Limitations and future research

This study has several limitations that offer directions for future research. First, the sample includes only listed agricultural firms in China, which may not fully represent the broader sector, particularly small and non-listed enterprises with different capacities for AI adoption and environmental management. Moreover, the sample size is relatively small (22 firms). While this firm-level evidence still provides valuable insights into AI's environmental impacts within the agricultural sector, the limited sample inevitably constrains the statistical power of the analysis and may weaken the external validity of the findings.

Second, while firm-level investment in AI hardware and software provides a practical proxy for AI application, it does not capture specific use cases. Different AI technologies—such as precision irrigation, pest detection, or automated spraying—may affect emissions through distinct pathways. This heterogeneity is not fully reflected in the current analysis.

Future research could address these limitations by incorporating data from non-listed enterprises or conducting field-level surveys to obtain more detailed information on AI usage patterns and expand the sample size. Additionally, disaggregating AI applications by function could help identify which technologies contribute most effectively to environmental performance, thereby offering more targeted policy and managerial implications.

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Data availability Data will be made available on request.

Conflict of interest: The 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.

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