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Does agricultural mechanization improve agricultural environmental efficiency?

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Improving agricultural environmental efficiency (AEE) is critical for sustainable and green agricultural advancement. However, there is limited research on the impact of agricultural mechanization on agricultural environmental efficiency. This study innovatively used micro-level survey data from the national fixed observation points of China's Ministry of Agriculture and Rural Affairs to employ a super-efficiency slacks-based measure (SBM) model with undesirable outputs for quantifying AEE. Additionally, a Tobit regression model was used to examine the influence of agricultural mechanization on AEE. Our findings revealed a "U-shaped" relationship between agricultural mechanization and AEE. Specifically, when the extent of mechanization fell below a particular threshold, any further increase adversely affected the AEE. Conversely, surpassing this threshold enhanced the AEE. This "U-shaped" effect was mediated by agricultural carbon emissions. Furthermore, our analysis indicated that relative to other village categories, the benefits of mechanization in elevating AEE are more pronounced in plain, agriculturally focused, and affluent villages. To promote the improvement of agricultural environmental efficiency, it is advisable to advance agricultural mechanization, reduce agricultural carbon emissions, and develop agricultural mechanization tailored to local conditions.

KEYWORDS

agricultural mechanization, environmental efficiency, China, moderating effect, SBM model

1 Introduction

Enhancing environmental efficiency in agriculture is pivotal for safeguarding food security and fostering sustainable eco-friendly growth within the sector. Since its reform in 1978, China's agricultural industry has garnered global attention owing to significant advancements in agricultural development in emerging economies. Nonetheless, the country's reliance on extensive farming practices has led to a range of environmental issues, including pollution, compromised crop quality, and land degradation. The agricultural and food production sector is facing immense pressure from other global challenges, such as water resource scarcity and the need to bolster energy security. This calls for the implementation of greener and more sustainable agricultural practices (Hamidinasab et al., 2023). As the ecological conditions within the agricultural landscape continue to deteriorate, exacerbated by the escalating use of agrochemicals, environmental pollution affecting soil, water, and air has emerged as a critical impediment to the sector's sustainability (Koul et al., 2022). The relationship between the economic outcomes of agricultural input production units and their environmental impacts is crucial for achieving sustainability (Hatim et al., 2023). In this context, increasing environmental efficiency in agriculture is an innovative strategy for mitigating both ecological pressures and resource scarcity, constituting a key pathway towards sustainable and green agricultural development (Rockström et al., 2017). Such improvements not only facilitate the optimal allocation of agricultural resources, thereby maximizing output and profitability with finite inputs, but also encourage the adoption of eco-conscious farming practices, which in turn reduce carbon emissions and enhance the resilience of agricultural ecosystems.

The mechanization of agriculture serves as a potent catalyst for enhancing environmental efficiency within the agricultural sector (Zhu et al., 2022a). By elevating the productivity of agricultural operations and mitigating adverse environmental repercussions, agricultural mechanization provides indispensable support for the sustainable development of agriculture. The advent of advanced agricultural machinery is progressively supplanting manual labor, thereby augmenting labor productivity (Jiang et al., 2020), fine-tuning the allocation of agricultural resources (Zhu et al., 2022a), and diminishing undesirable agricultural byproducts (Li and Guan, 2023). This culminates in a marked improvement in agricultural environmental efficiency (Zhou and Ma, 2022). Data from China's Ministry of Agriculture and Rural Affairs revealed that the comprehensive mechanization rate for crop cultivation increased from 52.3% in 2010 to 72.0% in 2021. The cultivation rates of wheat, corn, and rice were 97.3%, 90.0%, and 85.6%, respectively. In the period between 2010 and 2021, China had a substantial improvement in its environmental metrics. The area affected by soil erosion decreased from 356.92 million square kilometers in 2010 to 269.27 million square kilometers in 2021. Additionally, the proportion of surface water meeting Class I to III quality standards increased from 51.9% in 2010 to 84.9% in 2021. These trends suggest that agricultural mechanization in China likely contributes to enhanced environmental efficiency through resource conservation, pollution abatement, and ecological preservation.

Within the framework of this discourse, the present study aimed to investigate the driving forces behind the enhancement of environmental efficiency in agriculture through agricultural mechanization. Specifically, the study sought to address two pivotal questions: (1) To what extent, and in what manner, does agricultural mechanization influence environmental efficiency in the agricultural sector? (2) Are there regional disparities in the impact of agricultural mechanization on environmental efficiency within the agricultural landscape? By rigorously examining these questions, this study aimed to provide both theoretical insights and empirical evidence that may serve as valuable references for developing nations striving to accelerate agricultural mechanization and elevate environmental efficiency in their agricultural practices.

2 Literature review

A plethora of researchers, both within and outside national boundaries, have undertaken comprehensive investigations into agricultural environmental efficiency. These contributions serve as both theoretical foundations and empirical benchmarks for the research presented in this study. Extant literature predominantly bifurcates its focus into two key dimensions. First is the quantification of agricultural environmental efficiency. Researchers frequently employ micro-level data garnered through meticulous surveys to conduct efficiency assessments within localized geographical scopes. Noteworthy examples include studies that have used data from70 Saffron farms in Iran (Saeidi et al., 2022), rice farms in Korea (Nguyen et al., 2012), greenhouse tomato cultivation in Turkey (Turkten and Ceyhan, 2023), irrigated chickpea production in Iran (Nabavi-Pelesaraei et al., 2023) and shrimp aquaculture in Vietnam (Trang et al., 2023). Second, a subset of researchers have studied this topic from the macroscopic perspective, using datasets spanning nine East Asian nations (Le et al., 2019) or focusing on a provincial scale within China (Guo et al., 2022; Zhang et al., 2022). These studies not only quantified agricultural environmental efficiency but also delved into its spatiotemporal variations. In terms of methodological approaches, Some scholars have employed the methods of life cycle cost (LCC), life cycle assessment (LCA), and exergoeconomic analysis to analyze environmental and economic energy consumption (Hatim et al., 2023), researchers commonly use inventory analysis and the principles of material balance to account for agricultural pollutants. Subsequently, data envelopment analysis (DEA) is employed to quantify agricultural environmental efficiency (Hoang and Coelli, 2011). Data Envelopment Analysis (DEA) is the most widely used method in recent years for environmental optimization and assessment, as considered by many researchers (Nabavi-Pelesaraei et al., 2023). Undesired outputs, often termed 'non-beneficial outputs,' are assessed primarily through carbon emissions and agricultural nonpoint source pollution (Chen et al., 2021). In addition, some scholars have utilized machine learning models to assess agricultural environmental efficiency (Nabavi-Pelesaraei et al., 2023). Finally, the literature identified a range of factors that influence agricultural environmental efficiency. These include, but are not limited to, the scale of input factors (Zhu et al., 2022a), specific characteristics of agricultural households (Li et al., 2021), and utilization patterns of arable land (Chen and Xie, 2019).

In the field of agricultural environmental research, a subset of researchers has posited that the mechanization of agriculture plays a pivotal role in influencing the sector's environmental efficiency. From a theoretical standpoint, the advent of agricultural mechanization serves multiple purposes: it augments farmers' incomes (Qian et al., 2022), increases the efficiency of agricultural production (Jiang et al., 2020), revolutionizes traditional agricultural practices (Li and Guan, 2023), and enhances the ecological sustainability of the agricultural landscape (Zhou and Ma, 2022). Furthermore, interdisciplinary studies have delved into the multifaceted impact of agricultural mechanization by examining variables such as subsidy policies for machinery acquisition (Tian et al., 2021), migration patterns of agricultural labor (Shao et al., 2021), and carbon footprint of agricultural activities (Chen et al., 2021). While the prevailing academic consensus leans towards the positive environmental implications of agricultural mechanization, a segment of the academic community has unearthed evidence to the contrary. Specifically, they argued that escalated levels of mechanization correlate with a surge in energy consumption within the agricultural sector, thereby exacerbating carbon dioxide emissions and other forms of agricultural pollution (Daum and Birner, 2020). Concurrently, research conducted by Jiang et al. (2020).

Corroborates this notion by revealing a significant negative impact of agricultural mechanization on environmental energy performance, particularly in regions where mechanization is extensively adopted.

While recent studies offer foundational insights for this study, it notably lacks a comprehensive examination of the influence of agricultural mechanization on environmental efficiency within the agricultural sector. Three critical gaps warrant further investigation: (1) The current body of literature failed to integrate agricultural mechanization into discussions surrounding agricultural environmental efficiency. Despite the ubiquity of mechanized practices in modern agriculture, their specific ramifications and potential contributions to environmental efficiency remain underexplored. This gap underscores the need for additional empirical studies using robust datasets. (2) Existing research has predominantly investigated these topics through a macroscopic lens, relying chiefly on aggregate data to explore the correlation between agricultural mechanization and environmental efficiency. Although this approach provides a broad overview, it inadvertently neglects the idiosyncratic attributes of individual farming households, thereby limiting the granularity of the analysis. (3) Most studies operate under the assumption of a linear relationship between agricultural mechanization and environmental efficiency, thereby overlooking potential non-linear dynamics. Thus, the present study aimed to extend the analytical framework by incorporating a non-linear perspective to elucidate the intricate interplay between agricultural mechanization and environmental efficiency.

3 Theoretical analysis and research hypotheses

3.1 Agricultural mechanization and agricultural environmental efficiency

The efficiency of agricultural environmental management depends on the inputs and outputs associated with agricultural activities. Enhancements in agricultural environmental efficiency are primarily attributed to the optimization of resource utilization, amplification of output yields, and mitigation of environmental pollution (Zhu et al., 2022b). The introduction of mechanization in agriculture accelerates the integration of innovative technologies and equipment, thus facilitating the ongoing evolution of agricultural practices. Mechanized systems improve agricultural standardization, increase yield, and enhance the efficiency of environmental resource utilization in the agricultural sector. Advanced automated machinery and intelligent technology enable the precise collection of agricultural data and predictive analytics, thereby ensuring efficient resource allocation. This optimization minimizes waste and reduces losses in agricultural production (Zhu et al., 2022b). However, it is imperative to acknowledge the potential drawbacks of agricultural mechanization on environmental efficiency. The operation of mechanized equipment requires substantial fuel and energy consumption, which exacerbates greenhouse gas emissions. Moreover, the use of such machinery can increase soil compaction and diminish agricultural productivity. In the early stages of low agricultural mechanization, the investment in agricultural machinery can increase the cost of agricultural production. Due to the relatively low initial returns generated by the investment in agricultural machinery, it may not be sufficient to cover the initial costs. The role of economies of scale brought about by the development of agricultural mechanization is relatively weak. Additionally, low levels of agricultural mechanization may lead to resource wastage, including water resources and fertilizers. Inaccurate irrigation and fertilization methods can lead to the wastage of water resources and an increased risk of water pollution. Therefore, lower levels of agricultural mechanization may have a negative impact on agricultural environmental efficiency. However, as agricultural mechanization levels increase, the use of modern agricultural machinery can enable precise resource management, high yields, and environmentally friendly agricultural practices, thereby having a positive impact on agricultural environmental efficiency. It is evident that the relationship between agricultural mechanization and agricultural environmental efficiency is not a simple linear one. Agricultural mechanization at different stages of development may exhibit different directions of impact on agricultural environmental efficiency. Based on the above perspectives, we believe that the impact of agricultural mechanization on agricultural environmental efficiency may exhibit a "U-shaped" relationship, characterized by an initial negative effect followed by a positive effect. From this, we propose the first theoretical hypothesis:

Hypothesis 1: The impact of agricultural mechanization on agricultural environmental efficiency shows a nonlinear "U-shaped" relationship. That is, when the level of agricultural mechanization is low, it inhibits the improvement of agricultural environmental efficiency, but when the level of agricultural mechanization is high, it promotes the improvement of agricultural environmental efficiency.

3.2 The mediating role of agricultural carbon emissions

Agricultural carbon emissions are significant contributors to greenhouse gas emissions and their impact on the agricultural environment cannot be disregarded. Existing research indicates a close relationship between agricultural mechanization and carbon emissions. These emissions are undesirable by-products of agricultural production, and their reduction is crucial for enhancing agricultural environmental efficiency (Moghaddasi and Pour, 2016). Most researchers believe that agricultural mechanization has the potential to mitigate agricultural carbon emissions, thereby enhancing agricultural environmental efficiency. However, some researchers have observed that agricultural mechanization may lead to a moderate increase in carbon emissions (Jiang et al., 2020). First, the use of agricultural machinery consumes substantial energy and contributes to elevated carbon emissions. Additionally, it results in an excessive input of production factors such as fertilizers and pesticides (Tian et al., 2021). Nevertheless, eliminating outdated agricultural machinery and reducing fuel consumption can effectively reduce carbon emissions. Second, despite its associated carbon footprint,

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TABLE 1 Average agricultural environmental efficiency at the provincial level.

Province	Average	Province	Average
Zhejiang	0.3558	Shandong	0.0670
Guangdong	0.1852	Sichuan	0.0623
Jiangsu	0.1384	Anhui	0.0581
Liaoning	0.1211	Guangxi	0.0577
Hubei	0.1210	Guizhou	0.0564
Fujian	0.1096	Jiangxi	0.0556
Hebei	0.1055	Henan	0.0540
Tianjin	0.1039	Heilongjiang	0.0511
Hunan	0.0912	Gansu	0.0438
Jilin	0.0784	Chongqing	0.0341
Shanxi	0.0744	Beijing	0.0260
Neimenggu	0.0723	Shanxi	0.0215
Yunnan	0.0687	Xinjiang	0.0020
overall average	0.0852		

agricultural mechanization plays a pivotal role in improving the overall environmental efficiency of agricultural practices. On the one hand, employing advanced machinery and equipment enhances operational efficiency while significantly reducing energy consumption during farming practices, particularly when transitioning from traditional energy sources to cleaner alternatives, which aids in lowering carbon emission levels and subsequently elevating agricultural environmental efficiency. On the other hand, the operational mode and management approach adopted for implementing agricultural mechanization exert a considerable influence on carbon emissions; modernized machinery and equipment enable effective control over the pesticide and fertilizer quantities used. Employing appropriate tillage depths, irrigation levels, and scientifically sound fertilization methods can diminish the adverse impacts on soil quality and water resources caused by excessive inputs during farming activities, thus mitigating environmental pollution as well as agriculturally induced carbon emissions and ultimately increasing the overall agricultural environmental efficiency.

Hypothesis 2: Agricultural mechanization can affect agricultural environmental efficiency through carbon emission.

3.3 Influence of regional developmental status and environmental conditions

Agriculture is significantly influenced by the natural environment (Trang et al., 2023). Given the substantial variations in natural resource endowments and agricultural economic development across different regions of China, as well as the diverse levels of agricultural mechanization within these regions, regional disparities in agricultural environmental efficiency have emerged. The utilization of large-scale agricultural machinery and the magnitude of agricultural operations necessitate favorable terrain conditions. Flat and expansive land is more conducive to the deployment of agricultural machinery. Conversely, mountainous regions exhibit uneven topography and fragmented land, hampering the widespread adoption and implementation of mechanized agriculture. Consequently, while mechanization can enhance the environmental efficiency in agriculture, the potential to improve mechanization levels in mountainous areas remains limited, thereby constraining the role of agricultural machinery in enhancing environmental efficiency within these regions. The impact of agricultural mechanization on agricultural environmental efficiency is also influenced by the level of economic development. In suburban villages, attention is paid to the cultivation of cash crops such as vegetables and flowers; however, the mechanization level for these crops remains low. Therefore, the enhancement of agricultural mechanization has a more significant effect on improving the environmental efficiency of food crops in suburban areas. Impoverished villages, owing to local financial constraints and farmers' limited income levels, lack sufficient funds to upgrade their agricultural machinery even if they were willing to purchase it. Only when the economic conditions reach a certain level will there be improvements in purchasing agricultural machinery and embracing concepts related to agricultural environmental protection. Consequently, the positive impact of agricultural mechanization on enhancing agricultural environmental efficiency has become more pronounced. Based on the aforementioned analysis, we propose the following hypothesis:

Hypothesis 3: Agricultural mechanization has a significant disequilibrium effect on agricultural environmental efficiency, particularly in plains and hilly regions, as well as in agricultural villages and affluent communities.

4 Data and methodology

4.1 Data sources

The data used in this study are micro survey data from fixed observation points in rural areas of China. The survey data included more than 2,000 survey indicators of farmers, individuals, and cities, covering more than 300 administrative villages and 20,000 farmers in 31 provinces across the country (Yan et al., 2014). The survey data were rich and reliable, providing important support for this study to investigate the impact of agricultural mechanization on agricultural environmental efficiency. To mitigate the impact of factors like inflation, we adjusted relevant indicators using the Consumer Price Index for household consumption.

Data from fixed observation points in rural areas nationwide present challenges such as a significant time span and fluctuations in indicators. This study adopted the following methods to process data: First, the farmer-level data were matched with those of their family members and village-level data, while sample data lacking province and village codes were removed. Second, outlier treatments were conducted. Analysis of the data revealed that certain indicators exhibited abnormal values; for instance, gender data did not equal 0 or 1 and age exceeded 100 years. After addressing these issues, an unbalanced panel dataset comprising 19,146 samples was obtained.

4.2 Methods

4.2.1 Super efficiency slacks-based measure (SBM) model and variable selection

Compared to the traditional Data Envelopment Analysis (DEA) model, the SBM model can effectively address the estimation issue of slack variables in input-output variables (Tone, 2001). However, there will still be multiple valid measures of 1, which cannot be effectively differentiated and ranked (Xiao et al., 2023). The Super-SBM model, with an optimal efficiency value exceeding 1, represents a significant improvement over the conventional SBM model. Based on the method of Tone (2002), the Super-SBM model was used to calculate the AEE, which serves as an explained variable. The formulation of the proposed model is as follows:

$$\min \rho = \frac{\frac{1}{m}\sum_{i=1}^{m}\left(s^{x-}/x_{ik}\right)}{\frac{1}{d+u}\left(\sum_{s=1}^{d} s^{y+}\Big/ y_{sk}^{d} + \sum_{q=1}^{u} s^{u-}\Big/ y_{qk}^{u}\right)} \tag{1}$$

$$\begin{aligned} s.t.s^{x-} &\geq \sum_{j=1, j\neq k}^{n} x_{ij}\lambda_j, i = 1,\cdots,m \\ s^{y+} &\leq \sum_{j=1, j\neq k}^{n} y_{sj}^{d}\lambda_j, s = 1,\cdots,d \\ s^{u-} &\geq \sum_{j=1, j\neq k}^{n} y_{qj}^{u}\lambda_j, q = 1,\cdots,u \\ &\lambda_j \geq 0; j = 1,\cdots n; j\neq k \\ &s^{x-} \geq x_i; s^{y+} \leq y_s^d; s^{u-} \geq y_q^u \end{aligned} \tag{2}$$

In Eq. 1 and 2, s^{x-}, s^{y+}, and s^{u-} represent the relaxation variables of the factor input, expected output, and non-expected output, respectively. The nonzero values of these variables correspond to excessive factor input, insufficient expected output, and excessive non-expected output. For the decision units, $0 < \rho < 1$ indicates that the unit is inefficient. Values of $\rho \geq 1$ and $s^{x-} = s^{y+} = s^{u-} = 0$ signify that the decision-making unit is technically efficient.

4.2.2 Base model

Given that the agricultural environmental efficiency value, as measured by the super-efficiency SBM model, is non-negative truncated data and a restricted dependent variable, it is more appropriate to employ the Tobit model for maximum likelihood estimation. Accordingly, in this study, we constructed a panel Tobit model based on random effects. The basic form of the model is as follows:

$$Y_{it} = \begin{cases} Y_{it}^{*} & Y_{it}^{*} > 0 \\ 0 & Y_{it}^{*} \leq 0 \end{cases} \tag{3}$$

Using the Tobit model in Eq. 3, we can find the expression for the effects of agricultural mechanization on agricultural environmental efficiency:

$$AEE_{it} = \alpha_0 + \alpha_1 AM_{it} + \beta control_{it} + \varepsilon_{it} \tag{4}$$

In Eq. 4, AEE_{it} represents the explained variable of agricultural environmental efficiency, AM_{it} denotes the core explanatory variable of agricultural mechanization, $control_{it}$ is the control variable, ε_{it} signifies random error, i represents individual units, and t represents the time period. Natural logarithms were applied to the main variables of the model to address heteroscedasticity. Considering the possibility of a non-linear relationship between agricultural mechanization and agricultural environmental efficiency based on Tian et al. (2021), we introduced the quadratic term AM_{it}^2 for agricultural mechanization into our model, resulting in Eq. 5:

$$AEE_{it} = \alpha_0 + \alpha_1 AM_{it} + \alpha_2 AM_{it}^2 + \beta control_{it} + \varepsilon_{it} \tag{5}$$

4.2.3 Intermediate effect model

According to the results of the theoretical analysis, agricultural mechanization was expected to affect agricultural environmental efficiency through its influence on agricultural carbon emissions. To examine this mediation effect, we established the following empirical model, with reference to the methodology of Wen and Ye (2014). Considering the potential nonlinearity of the relationship between agricultural mechanization and carbon emissions, we incorporated a quadratic term for agricultural mechanization into Eq. 6. Here, *carbon_emissions* in Eq. 7 and Eq. 8 represent the mediating variables of agricultural carbon emissions.

$$AEE_{it} = \alpha_0 + \alpha_1 AM_{it} + \alpha_2 AM_{it}^2 + \beta control_{it} + \varepsilon_{it} \tag{6}$$

$$carbon\_emission_{it} = \alpha_3 + \alpha_4 AM_{it} + \alpha_5 AM_{it}^2 + \beta_1 control_{it} + \varepsilon_{it} \tag{7}$$

$$AEE_{it} = \alpha_6 + \alpha_7 AM_{it} + \alpha_8 AM_{it}^2 + \alpha_9 carbon\_emission_{it} + \beta_2 control_{it} + \varepsilon_{it} \tag{8}$$

4.3 Measurement and analysis of agricultural environmental efficiency

In this study, six inputs (land, labor, capital, fertilizer, pesticide, and agricultural film) were selected as input indicators, agricultural income as the expected output, and agricultural carbon emissions as the non-expected output. Land was measured as the total sown area of each farmer's crop; labor force was measured by the number of people in the labor force in rural households; capital was measured as the original value of productive fixed assets owned by farmers at the end of the year; and chemical fertilizers, pesticides, and agricultural films were measured based on their amounts purchased by farmers in the current year. In this study, agricultural carbon emissions mainly included fertilizers, pesticides, agricultural films, diesel oil, plowing, and irrigation, with carbon emission coefficients of 0.8956 (kg/kg), 4.9341 (kg/kg), 5.18 (kg/kg), 0.5927 (kg/kg), 312.6 (kg/km2), and 25 (kg/hm2), respectively. In this paper, the calculation method of Intergovernmental Panel on Climate Change (IPCC) was used for reference, and the emission coefficient was multiplied by the

TABLE 2 Description of variables and descriptive statistics.

Variable	Variable declaration	Obs	Mean	SD	Min	Median	Max
AEE	Calculated data	19146	0.093	0.162	0.000	0.035	1.160
AM	Number of power machines for agriculture, forestry, animal husbandry, and fishery	19146	0.585	0.497	0.000	0.693	4.159
internet	Internet access = 1, no = 0	19146	1.838	0.369	0	1	1
gender	Male = 1, female = 0	19146	1.457	0.498	1	1	2
age	Specific age (years)	19146	37.442	19.253	0	38	80
edu	Years of schooling (years)	19146	6.926	3.442	0	8	20
income	Logarithm of a family's annual net income in yuan	19146	10.572	0.770	0.000	10.583	13.626

amount of use or area to calculate the total agricultural carbon emission.

The agricultural environmental efficiency of the studied provinces was measured using the Maxdea software. The results revealed that 90% of the farmers' data had an agricultural environmental efficiency below 0.23, with an average value of 0.09. These findings were in accordance with those of previous studies that utilized microsurvey data to measure agricultural environmental efficiency (Chang, 2020), suggesting a generally low level of agricultural environmental efficiency. As shown on Table 1, the top three provinces in agricultural environmental efficiency are Zhejiang, Guangdong, and Jiangsu, respectively. Among the bottom ten, all except Beijing are provinces in the central and western regions of China. It can be observed that there is a pattern where eastern provinces have higher agricultural environmental efficiency, while central and western provinces have lower efficiency. Therefore, it is necessary to discuss the impact of agricultural mechanization on agricultural environmental efficiency in different regions in future research.

4.4 Variable description

(1) Dependent variable: The primary explanatory variable in this study was agricultural environmental efficiency (AEE), measured using a super-efficient SBM model incorporating non-expected output.

(2) Independent variable: Agricultural mechanization (AM). Following the approach of Sun et al. (2022), this study measured agricultural mechanization by considering the number of power machines used in agriculture, forestry, husbandry, and fishery activities.

(3) Mediating variable: Agricultural carbon emissions. In this study, agricultural carbon emissions were selected as the mediating variable.

(4) Control variables: Drawing from existing literature and available data, this study included several control variables: age, represented by the age of household members engaged in farming; gender, indicated by male = 1 and female = 0 for farmers' family members; years of schooling (edu), denoted by educational attainment of household members; internet access (internet), expressed as whether or not the household has internet connectivity, with 1 indicating access and 0 indicating no access; and household income (income), represented by natural logarithm transformation of annual net income (in yuan). Table 2 provides the detailed descriptions and descriptive statistics for these variables.

5 Results and discussion

5.1 Baseline regression analysis

First, to mitigate the potential impact of multicollinearity on the regression results, we assessed the presence of multicollinearity. The test results revealed that all the correlation coefficients among the variables were below 0.5, suggesting a preliminary absence of multicollinearity in the model. Second, using variance inflation factor (VIF) analysis as an additional measure, we found that each variable exhibited a VIF value lower than 10, with a mean VIF of 2.1, further confirming the absence of multicollinearity in the model. Table 3 presents the estimated effects of agricultural mechanization on agricultural environmental efficiency.

The insignificant LR value suggested that a mixed Tobit model is more appropriate for assessing the impact of agricultural mechanization on agricultural environmental efficiency. In Table 3, Models (1)–(3) display the regression outcomes for the primary term of agricultural mechanization, including both linear and quadratic terms, as well as the inclusion of control variables. Model (1) examines the relationship between agricultural mechanization and agricultural environmental efficiency, whereas Model (2) investigates the non-linear effect by incorporating a quadratic term for agricultural mechanization based on Model (1). Finally, Model (3) incorporates all the control variables into Model (2). Our analysis of how agricultural mechanization affects agricultural environmental efficiency is outlined below.

First, the impact of agricultural mechanization on agricultural environmental efficiency was evident. As shown in Table 3, the estimated coefficient for the primary term of agricultural mechanization was negative, whereas the estimated coefficient for the quadratic term was positive. Both coefficients passed the significance level test at the 1% level, indicating a clear non-linear relationship between agricultural mechanization and agricultural environmental efficiency. Specifically, agricultural environmental efficiency initially declined and then increased with continuous development of agricultural mechanization. The estimates in Table 3 show that the inflection point value of the impact of agricultural mechanization on agricultural environmental

TABLE 3 Results of baseline regression.

	(1) AEE	(2) AEE	(3) AEE
AM	−0.0539***	−0.1026***	−0.1117***
	(−21.9359)	(−20.2467)	(−21.2045)
AM^2		0.0335***	0.0383***
		(14.1809)	(15.2164)
internet			0.0170***
			(5.4292)
gender			0.0076***
			(3.2722)
age			0.0002***
			(2.7161)
edu			0.0034***
			(10.2990)
income			−0.0151***
			(−6.4971)
_cons	0.1242***	0.1329***	0.2229***
	(55.6152)	(52.0794)	(8.3712)
var(e.AEE)	0.0255***	0.0253***	0.0250***
	(32.9829)	(32.9697)	(32.6275)
N	19146	19146	19146
Pseudo R2	−0.0345	−0.0425	−0.0588

Note: ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively, with the t-statistics in parentheses.

efficiency was 1.4582. Specifically, when the level of agricultural mechanization is below 1.4582, it exerts a negative influence on agricultural environmental efficiency, whereas when it exceeds 1.4582, it has a positive effect on improving this efficiency. This suggests that initial investments in agricultural mechanization do not contribute to enhancing agricultural environmental efficiency; however, once a certain threshold is reached, further improvements in its level will lead to enhanced environmental performance within agricultural practices. The first plausible explanation for this phenomenon is that the development of agricultural mechanization needs to be a gradual process to effectively promote and enhance overall agricultural environmental efficiency. During stages characterized by relatively low levels of mechanization, increased input of machinery may escalate the production costs and potentially hinder improvements in environmental performance associated with agricultural modernization efforts. The second possible explanation is that compared to stages marked by high levels of mechanization, stages marked by lower levels of mechanization are often accompanied by reduced production efficiencies, resulting in energy waste and pollution within the farming sector, which is detrimental to advancing overall ecological sustainability within agriculture.

Second, the impact of agricultural mechanization on agricultural environmental efficiency varied across the models. As shown in Table 3, in Models (1) to (3), when only the primary term of agricultural mechanization is included in the model, it has a significant negative effect on agricultural environmental efficiency at the 1% significance level. However, when both the primary and secondary terms are considered, the relationship between agricultural mechanization and agricultural environmental efficiency is 'U-shaped', which is also significant at the 1% significance level. This suggests that examining solely the linear relationship between these two variables is insufficient because of the complex non-linear relationship that can be better captured by adding the quadratic term of agricultural mechanization to Model (2). Additionally, after controlling for other factors in Model (3), we found that the estimated coefficient and significance remained stable, indicating that this relationship is relatively robust.

Third, the influence of the controlling variables on agricultural environmental efficiency is noteworthy. As evident from the estimated results in Table 3, the impact of internet access on agricultural environmental efficiency was significantly positive at the 1% significance level. This implied that rural households' connectivity to the internet can effectively enhance agricultural environmental efficiency. One plausible explanation for this phenomenon lies in the "internet + agriculture" environment, where internet usage facilitates a profound integration between green agricultural technology and rural households. Moreover, age exhibited a significant positive effect on agricultural environmental efficiency at the 1% significance level, indicating that older household heads are more likely to promote improvements in

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TABLE 4 Robustness test results.

	(1) Alternate explanatory variable	(2) Alternate estimation method	(3) Excluding the town government
value	−0.0161***		
	(−10.3392)		
value2	0.0009***		
	(5.3301)		
internet	0.0203***	0.0170***	0.0194***
	(6.4238)	(5.4282)	(5.5016)
gender	0.0075***	0.0076***	0.0087***
	(3.2077)	(3.2716)	(3.4192)
age	0.0001**	0.0002***	0.0001
	(2.3188)	(2.7157)	(1.0591)
edu	0.0034***	0.0034***	0.0026***
	(10.0489)	(10.2971)	(7.2145)
income	−0.0148***	−0.0151***	−0.0030
	(−6.2808)	(−6.4959)	(−1.1551)
AM		−0.1117***	−0.1059***
		(−21.2007)	(−18.0876)
AM^2		0.0383***	0.0339***
		(15.2136)	(12.8043)
_cons	0.2221***	0.2229***	0.1014***
	(8.2022)	(8.3697)	(3.3395)
var(e.AEE)	0.0258***		0.0251***
	(30.9674)		(28.0235)
N	19146	19146	16115
Pseudo R2	−0.0708		−0.0557
Adj. R2		0.0458	

Note: ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively, with the t-statistics in parentheses.

this aspect. This could be attributed to their accumulated experience in managing agricultural production, which is advantageous for enhancing agricultural environmental efficiency. Gender also exerted a positive and significant influence on agricultural environmental efficiency at the 1% significance level. This suggested that male-peasant households contribute more towards improving this efficiency. A possible rationale behind this finding is rooted in men's predominant role as laborers in agriculture, coupled with their greater land rights and resource control capabilities, which enable them to leverage their physical strength and decision-making advantages towards enhancing both output and overall effectiveness within an agrarian context. The influence of educational level on agricultural environmental efficiency was positive and significant at the 1% significance level, indicating that a higher educational level among rural household heads can enhance agricultural environmental efficiency. One plausible explanation for this phenomenon is that the educational attainment of household heads affects their acceptance and application of green agricultural knowledge and skills, thereby improving agricultural environmental efficiency. Additionally, highly educated household heads are more inclined to engage in business activities outside their households, leading to greater utilization of agricultural machinery in production processes and consequently enhancing agricultural environmental efficiency. Furthermore, the influence of household income on agricultural environmental efficiency was found to be negative and significant at the 1% significance level, suggesting that higher household income has a detrimental effect on improving agricultural environmental efficiency. This could be attributed to the fact that, as household income increases, the tendency to prioritize cash crop cultivation over food crops increases as well. This intensifies the demand for pesticides, fertilizers, and water resources without ultimately contributing to the improvement in the overall agricultural environmental efficiency.

5.2 Robustness test

Based on the aforementioned analysis, it is evident that enhancing the level of agricultural mechanization can effectively enhance agricultural environmental efficiency. To further validate the empirical findings of this study, robustness tests were conducted using the methods outlined in Table 4.

First, explanatory variables should be modified. In this section, the values of agriculture, forestry, animal husbandry, and fishery machinery can serve as substitute variables for agricultural mechanization. The total value of agriculture, forestry, animal husbandry, and fishery machinery can be used to quantify the scale and level of agricultural mechanization. A higher total value of machinery typically indicates increased usage in agricultural production and suggests a higher level of agricultural mechanization for farmers. Variable settings and measurement model selection were consistently aligned with the benchmark model. As is evident from the estimation results in column (1) of Table 4, the impact of agricultural mechanization on agricultural environmental efficiency was characterized by a "U-shaped" relationship, without any significant change observed in the estimated coefficient for agricultural mechanization. This finding underscores the robustness of our conclusions.

Furthermore, we implemented a changed estimation method. In this section, we employed an Ordinary Least Squares (OLS) model for the re-estimation to ensure consistency with the benchmark model in terms of variable setting and measurement model selection. The estimation results presented in column (2) of Table 4 confirm that agricultural mechanization continues to exhibit a "U-shaped" relationship with agricultural environmental efficiency. Notably, the estimated coefficient of agricultural mechanization remained unchanged and statistically insignificant, confirming the robustness of our findings.

Third, the samples located in the town government were excluded from robustness tests to ensure the robustness and universality of the study, as their location reflects the economic and geographical conditions of the farmers' residences. The variable settings and measurement model selection were consistent with those of the benchmark model. As is evident from the estimation results in column (3) of Table 4, agricultural mechanization still exhibited a "U-shaped" relationship with agricultural environmental efficiency and there was no significant change in the estimated coefficient of agricultural mechanization. This again indicated that the findings of the study are robust.

5.3 Mechanism analysis

According to theoretical analysis, agricultural carbon emissions play a crucial intermediary role influencing agricultural environmental efficiency during the process of agricultural mechanization. However, empirical verification is required to determine whether agricultural mechanization affects agricultural environmental efficiency through its impact on agricultural carbon emissions. Table 5 presents the estimated results of the intermediary effect model.

As shown in the estimation results presented in column (2) of Table 5, the primary term coefficient of agricultural mechanization was negative, whereas the secondary term coefficient was positive, both passing a significance level of 1%. This indicated that agricultural mechanization had a significant impact on agricultural carbon emissions, and there was an obvious non-linear relationship between them. Specifically, as agricultural mechanization increased continuously, agricultural carbon emissions first decreased and then increased. After adding agricultural carbon emissions to column (3) of Table 5, the estimated coefficients for both the primary and secondary terms remained negative and positive, respectively, at a significance level of 1%, consistent with the baseline regression. These findings suggested that agricultural carbon emissions play an intermediary role in the process by which agricultural mechanization affects environmental efficiency within agriculture, and the "U-shaped" impact caused by such emissions explains why environmental efficiency varies with the levels of mechanization. A possible explanation for this phenomenon lies in two factors. First, when mechanization levels are low, small-to medium-sized machinery tends to be used more frequently, resulting in higher energy consumption per unit area, which leads to increased carbon emissions, thereby reducing environmental efficiency. Second, when mechanization levels are high, large-scale production can be carried out, improving energy utilization rates and leading to reduced carbon emissions, thus enhancing environmental efficiency.

6 Expansive analysis

Because of China's vast territory, diverse topography, and varying economic structures across different regions, the country exhibits significant regional disparities in its economic structure. To further investigate the heterogeneity of the impact of agricultural mechanization on agricultural environmental efficiency, this section explores the influence of agricultural machinery on this efficiency from a disequilibrium perspective.

6.1 Regional heterogeneity

China covers an extensive territory characterized by significant heterogeneity in natural resource endowment and agricultural economic development across its eastern, central, and western regions. Considering the substantial diversity of China's agricultural regions, there are notable regional disparities in the level of agricultural mechanization. Therefore, this study partitioned the sample data into subsamples based on the eastern, central, and western regions to investigate variations in the impact of agricultural mechanization on agricultural environmental efficiency.

As can be seen from Table 6, the impact of agricultural mechanization on agricultural environmental efficiency in the eastern and central regions was consistent with the whole sample, presented a "U-shaped" relationship, and was significant at the 1% significance level; however, the impact on agricultural environmental efficiency in western China did not pass the significance test. This showed that agricultural mechanization can improve agricultural environmental efficiency in the eastern and central regions, but its effect on the agricultural environmental efficiency in the western region is not as pronounced. One possible explanation for this is that the terrains in the eastern and central regions are more suitable for implementing

TABLE 5 Mediation effect test results.

	(1) AEE	(2) carbon_emission	(3) AEE
AM	−0.1117***	11.1877***	−0.0853***
	(−21.2045)	(8.5994)	(−15.8247)
AM²	0.0383***	−3.6187***	0.0291***
	(15.2164)	(−5.3731)	(11.7290)
internet	0.0170***	7.0481***	0.0276***
	(5.4292)	(9.3096)	(9.3131)
sex	0.0076***	1.0184**	0.0081***
	(3.2722)	(2.3277)	(3.5147)
age	0.0002***	0.0180	0.0001**
	(2.7161)	(1.4742)	(2.4821)
edu	0.0034***	0.0982	0.0035***
	(10.2990)	(1.4954)	(10.7585)
income	−0.0151***	−3.7720***	−0.0130***
	(−6.4971)	(−6.3096)	(−5.7088)
carbon_emission			−0.0135***
			(−11.2070)
_cons	0.2229***	44.5446***	0.2588***
	(8.3712)	(6.2321)	(9.6729)
var(e.AEE)	0.0250***		0.0246***
	(32.6275)		(33.1050)
var(e.zhongjie)		133.6043***	
		(5.7291)	
N	19146	19146	19146
Pseudo R²	−0.0588	0.1456	−0.0802

Note: ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively, with the t-statistics in parentheses.

agricultural mechanization for agricultural production. The eastern region is relatively flat, with more plains and concentrated land, making it easier to implement agricultural mechanization. On the other hand, the terrain in the western region is complex, and many traditional agricultural machines cannot be used in these terrain conditions, making it difficult to promote agricultural machinery in this region. Second, agricultural mechanization depends on irrigation facilities and an adequate supply of water resources; the western region generally faces water shortages, which also limits the promotion and application of agricultural mechanization in this region.

6.2 Topographic heterogeneity

The efficiency of agricultural environmental management is not solely influenced by external production tools but is also constrained by terrain conditions. Large-scale agricultural machinery and operations necessitate favorable terrain, particularly flat and expansive lands that facilitate mechanization. Thus, this study categorized the sample data into plains, hills, and mountains based on terrain conditions to investigate the variations in the impact of agricultural mechanization on environmental efficiency across different landscapes. The regression results are presented in Table 7.

As depicted in Table 7, agricultural mechanization significantly impacts agricultural environmental efficiency in both plain and hilly areas at a significance level of 1%, exhibiting a "U-shaped" relationship that aligns with the estimated results of baseline regression. However, the impact of agricultural mechanization in mountainous areas failed to meet the significance limit, indicating that enhancing the level of agricultural mechanization in such regions does not substantially enhance local agricultural environmental efficiency. One possible explanation is that plains

TABLE 6 Regional regression results.

	(2) Eastern	(3) Central	(4) Western
AM	−0.1192***	−0.0400***	−0.0070
	(−12.7919)	(−5.5366)	(−0.6887)
AM^2	0.0375***	0.0186***	−0.0061
	(6.8687)	(5.8929)	(−1.3250)
internet	0.0222***	0.0119***	0.0378***
	(4.1178)	(3.2708)	(9.3318)
gender	0.0127***	0.0020	−0.0002
	(2.8736)	(0.7114)	(−0.0688)
age	0.0004***	−0.0001	−0.0002**
	(3.3865)	(−0.8005)	(−2.5542)
edu	0.0050***	0.0012***	−0.0006
	(8.8694)	(2.6379)	(−1.1038)
income	−0.0172***	−0.0111***	−0.0109***
	(−4.5522)	(−3.0973)	(−4.6464)
_cons	0.2352***	0.1701***	0.1309***
	(5.4438)	(4.0886)	(4.5523)
var(e.AEE)	0.0376***	0.0168***	0.0063***
	(27.6098)	(16.1848)	(15.1080)
N	8214	8537	2395
Pseudo R2	−0.1451	−0.0072	−0.0140

Note: ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively, with the t-statistics in parentheses.

and hilly areas are relatively flat with minimal elevation differences, making them more suitable for the efficient implementation of agricultural mechanization practices. Second, mountainous terrain, characterized by fragmentation and uneven distribution of cultivated land, lacks the conditions conducive to large-scale machinery farming. Consequently, improving the level of agricultural mechanization has become comparatively challenging in these regions, resulting in a relatively minor impact on their overall agricultural environmental efficiency.

6.3 Village heterogeneity

To investigate the differential impact of agricultural mechanization on agricultural environmental efficiency between suburban and rural villages, this study categorized villages into suburban and rural based on their location at the urban-rural interface and further examined the disparities in the effects of agricultural mechanization on agricultural environmental efficiency in these areas. The estimation results from Subsamples (4) and (5) in Table 7 revealed that agricultural mechanization had a significant "U-shaped" effect on improving agricultural environmental efficiency in rural villages at the 1% significance level. Conversely, although the direction of impact was consistent for suburban villages, it failed to reach statistical significance. These findings suggested that agricultural mechanization can enhance the environmental efficiency of rural agriculture to a greater extent than that of suburban villages. One possible explanation for this is that the labor force tends to concentrate in rural areas, where heavy farming tasks can be replaced by machinery, optimizing resource allocation and consequently improving environmental efficiency. Additionally, as important suppliers of urban agricultural products, rural areas face diverse demands for refined crops, necessitating complex planting structures. This complexity not only facilitates advancements in agricultural mechanization but also contributes to improved environmental efficiency.

6.4 Economic development level heterogeneity

The impact of agricultural mechanization on agricultural environmental efficiency is influenced by the degree of village economy development (Chen et al., 2022). To analyze this relationship under different economic levels, the sample data were categorized into five grades based on the economic

TABLE 7 Regression results by terrain and village type.

	(1) Plains	(2) Hills	(3) Mountains	(4) Suburban villages	(5) Rural villages
AM	−0.0258***	−0.0474***	−0.1587***	−0.0177	−0.1110***
	(−2.8909)	(−5.5807)	(−15.4644)	(−0.6665)	(−20.2594)
AM^2	0.0012	0.0247***	0.0414***	0.0152	0.0370***
	(0.2853)	(7.1458)	(6.4311)	(1.2353)	(14.1344)
internet	0.0112***	0.0176***	−0.0050	−0.0050	0.0185***
	(3.0582)	(3.4297)	(−0.4610)	(−0.4056)	(5.5512)
sex	0.0017	0.0018	0.0165***	0.0021	0.0080***
	(0.6082)	(0.4152)	(3.2013)	(0.4945)	(3.0440)
age	−0.0000	0.0001	0.0005***	−0.0003***	0.0002***
	(−0.5643)	(1.0809)	(4.0499)	(−2.6139)	(3.1186)
edu	0.0009*	0.0030***	0.0046***	−0.0016*	0.0039***
	(1.8294)	(4.9234)	(7.1533)	(−1.8335)	(10.7593)
income	0.0014	−0.0087*	−0.0254***	−0.0285***	−0.0144***
	(0.5589)	(−1.7671)	(−5.6840)	(−7.1288)	(−5.7562)
_cons	0.0526*	0.1274**	0.3748***	0.4065***	0.2089***
	(1.8089)	(2.2363)	(7.0773)	(7.6932)	(7.3026)
var(e.AEE)	0.0153***	0.0226***	0.0373***	0.0110***	0.0280***
	(15.5470)	(15.2395)	(24.4906)	(8.0779)	(29.8788)
N	7820	5111	6215	2439	16707
Pseudo R2	−0.0059	−0.0148	−0.2880	−0.0142	−0.0804

Note: ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively, with the t-statistics in parentheses.

development level and living standards of farmers: high, upper-middle, middle, lower-middle, and low.

As is evident from the estimated findings presented in Table 8, significant variations were observed in the impact of agricultural mechanization on agricultural environmental efficiency across regions with varying degrees of economic development. Notably, the influence of agricultural mechanization on agricultural environmental efficiency was relatively limited in impoverished villages, whereas it had a pronounced effect in affluent villages. One plausible explanation for this disparity is that prosperous villages possess greater financial and resource capabilities, facilitating the adoption and promotion of agricultural mechanization. Additionally, these villages often benefit from a well-established infrastructure, which further facilitates the implementation of mechanized farming practices. Conversely, when economic development levels are relatively low, farmers' income constraints hinder their ability to invest adequately in upgrading agricultural mechanization despite recognizing its potential benefits for improving environmental conditions, resulting in a comparatively smaller impact on agricultural environmental efficiency within poor villages.

In addition, this paper also has the following limitations, which point to future research directions:

(1) This study investigates the impact of agricultural mechanization on agricultural environmental efficiency from the perspective of micro-level farmers in China. In the future, research can be conducted from the perspective of specific regions in China or other countries.
(2) The micro-level survey data from fixed observation points in rural China used in this paper are limited by the data's constraints. The research dataset is concentrated in certain fixed years and provinces, and it is an unbalanced panel dataset. In the future, further exploration and improvement of the research can be achieved by using more appropriate datasets.
(3) Agricultural environmental efficiency is influenced by various factors related to farm characteristics. However, due to limitations in the dataset collected in this study, the factors considered are relatively limited. Future research can explore a broader range of influencing factors.

7 Conclusions and policy implications

Promoting agricultural mechanization is a crucial approach to enhancing agricultural environmental efficiency; however, no

TABLE 8 Regression by economic level.

	(1) High	(2) Upper-middle	(3) Middle	(4) Lower-middle	(5) Low
AM	−0.2734***	−0.1036***	−0.0953***	−0.1853***	0.1062***
	(−12.1339)	(−8.9633)	(−15.0597)	(−10.2743)	(3.8864)
AM^2	0.0823***	0.0330***	0.0318***	0.0814***	−0.0462***
	(4.5448)	(6.5071)	(10.6859)	(8.1496)	(-3.8434)
internet	0.0458*	−0.0150**	0.0372***	−0.0066	0.0276**
	(1.8539)	(−2.4060)	(9.2813)	(−0.6459)	(2.0851)
sex	−0.0090	0.0001	0.0098***	0.0053	0.0050
	(−0.2660)	(0.0267)	(3.3189)	(0.5493)	(0.3163)
age	−0.0008	−0.0002*	0.0001	0.0009***	0.0001
	(−0.8582)	(−1.8585)	(1.4538)	(3.1280)	(0.5247)
edu	−0.0045*	0.0021***	0.0029***	0.0050***	0.0022
	(−1.9240)	(2.8902)	(7.4791)	(3.3046)	(1.1393)
income	0.0600	−0.0171***	0.0074**	−0.0770***	−0.0059
	(1.3910)	(−4.4828)	(2.3363)	(−10.2281)	(−0.6778)
_cons	−0.4020	0.3382***	−0.0587*	0.9022***	0.0359
	(−0.8122)	(7.0405)	(−1.6864)	(9.9205)	(0.2939)
var(e.AEE)	0.0268*	0.0215***	0.0244***	0.0421***	0.0133**
	(1.9131)	(13.9321)	(24.3362)	(12.8070)	(2.2261)
N	102	5195	11797	1818	234
Pseudo R2	−0.2040	−0.0422	−0.0557	−14.3370	−0.0628

Note: ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively, with the t-statistics in parentheses.

relevant literature has directly investigated the relationship between agricultural mechanization and agricultural environmental efficiency. In this study, we incorporated agricultural mechanization into the measurement framework of agricultural environmental efficiency using fixed observation point data from rural areas. We used the super-efficiency SBM model to re-evaluate agricultural environmental efficiency and analyze how it is affected by agricultural mechanization. Our findings revealed a significant "U-shaped" relationship between agricultural mechanization and agricultural environmental efficiency, this somewhat extends the findings of Vortia et al. (2021) and Xu Qh (2022), among others, that agricultural mechanization can boost agricultural production. The lowest level of agricultural environmental efficiency was recorded when the level of mechanization reached 1.4582. However, beyond this critical value, further increases in mechanization lead to improvements in the environmental performance of agricultural practices. This "U-shaped" effect can be attributed to agricultural mechanization's influence on reducing carbon emissions from agriculture. Moreover, our findings indicated that the impact of agricultural mechanization on improving agricultural environmental performance was more pronounced in plains and hilly areas as well as in agriculturally focused villages with higher economic development levels. The findings also support the studies of Zou and Wu (2017) and Jena and Tanti et al. (2023) on the existence of differences in the impact of agricultural mechanization on agricultural production in different topographic areas. Based on these conclusions, we describe the implications and measures that should be implemented in developing countries that aim to promote agricultural mechanization and improve their overall ecological sustainability.

First, agricultural mechanization should be promoted and agricultural environmental efficiency should be enhanced. The government should establish a dedicated fund to support the research, development, and production of agricultural mechanization equipment. Collaborative efforts among production units, universities, and research institutions should be facilitated while encouraging the widespread participation of production units, universities, research organizations, and agricultural machinery service providers in technology dissemination. Intelligent and sustainable upgrading of agricultural machinery should be expedited by the development of energy-efficient and eco-friendly products that reduce carbon emissions from the machinery itself to advance the improvements in agricultural environmental efficiency. Preferential policies should be implemented to increase the financial support for agricultural mechanization while facilitating cross-regional machinery operation to ensure policy backing for its development. Technical training programs should be strengthened for farmers to enhance their operational proficiency and maintenance skills while addressing the challenges encountered during the use of agricultural machinery, thereby fostering the active engagement of farmers in promoting mechanization. Energy conservation and emission reduction measures should be promoted within the realm of agriculture by advocating low-carbon farming practices and ecological agricultural models to elevate overall agricultural environmental efficiency.

Second, agricultural mechanization should be promoted and agricultural carbon emissions mitigated. The utilization of agricultural waste resources should be actively encouraged, the development of rural renewable energy sources fostered, conservation farming practices advocated, high-standard farmland construction strengthened, and the carbon sequestration capacity of farmland soils enhanced. Furthermore, farmers should be incentivized to adopt energy-efficient and environmentally friendly agricultural machinery and equipment while reducing excessive water resource usage and fertilizer application in agriculture to minimize agricultural carbon emissions. To achieve this goal, we propose establishing a subsidy mechanism that rewards farmers based on their level of agricultural mechanization and the amount of carbon emission reduction achieved. This approach aims to encourage farmers to adopt clean energy equipment options while optimizing the allocation and management of agricultural machinery resources for efficient resource utilization and reduced agriculture-related carbon emissions. Additionally, we aim to vigorously promote green and energy-saving technologies in agriculture by providing cost-effective and high-quality services related to agricultural machinery. By supporting innovation in new energy-based agricultural machinery products through appropriate policies, the introduction of advanced equipment into practice can effectively lower carbon emissions during various stages of crop cultivation, thus paving the way toward low-carbon development in agriculture.

Third, agricultural mechanization should be promoted according to local conditions. Tailored agricultural mechanization policies should be implemented based on specific agricultural characteristics and environmental conditions in different regions. Farmland improvement in hilly and mountainous areas should be enhanced, land fragmentation reduced, the transformation of farmland into machine-friendly terrain in these regions facilitated, the operational capacity for large- and medium-sized agricultural machinery expanded, innovation in agricultural machinery and equipment expedited, and widespread adoption of mechanization technology in hilly and mountainous areas encourage. This will enhance the adaptability and efficiency of agricultural machinery and equipment as well as advance the modernization of agricultural production. Strengthening infrastructure development for agricultural mechanization is crucial in economically underdeveloped areas and should be done by focusing on investments toward rural mechanized roads and electromechanical irrigation stations to improve the fundamental conditions for agricultural production. Furthermore, the agricultural mechanization technology should be popularized to assist farmers in enhancing their operational skills regarding the use of farming machinery while promoting its widespread adoption. Given that suburban areas have a more complex planting structure, it is essential to prioritize the development of mechanisms for processing, preserving, storing, and transporting both primary crops and efficient cash crop production.

Data availability statement

The raw data supporting the conclusion of this article will be made available by the authors, without undue reservation.

Author contributions

FY: Conceptualization, Methodology, Writing–original draft. GD: Funding acquisition, Project administration, Supervision, Writing–review and editing. SC: Software, Visualization, Writing–review and editing. XS: Investigation, Resources, Validation, Writing–review and editing.

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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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