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EDITED BY
Amar Razzaq,
Huanggang Normal University, China

REVIEWED BY
Shifadjzic Khan,
Kyungpook National University,
Republic of Korea
Handong Lyu,
Hohai University, China

*CORRESPONDENCE
Shaochun Zhang
✉ zhangshaochun@webmail.hzau.edu.cn

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Linking land policy to food system sustainability: farm scale effects on smart irrigation adoption in northern China

Shaochun Zhang[1,2,3]* and Hang Xiong[1]

[1]College of Economics and Management, Huazhong Agricultural University, Wuhan, China, [2]College of Economics, Inner Mongolia University of Finance and Economics, Hohhot, China, [3]Inner Mongolia Rural Pastoral Area Management Capacity Modernization Research Base, Hohhot, China

Smart irrigation systems represent a critical innovation for advancing sustainable food production in water-scarce regions. As global food systems face mounting pressure from climate change and resource constraints, understanding the drivers of water-efficient technology adoption becomes essential for achieving both food security and environmental sustainability. This study investigates the adoption of smart irrigation systems among maize farmers in northern China, examining the roles of land consolidation and large-scale operation within the broader context of sustainable agricultural development. Drawing on a theoretical framework of expected profit maximization, we analyze household survey data from 803 maize farmers using drip irrigation in Inner Mongolia. Results demonstrate that both land consolidation and large-scale operation significantly promote smart irrigation adoption, though effects vary by institutional support mechanisms, regional suitability, and water resource endowment. These findings contribute to literature on sustainable food systems by revealing how land tenure arrangements and farm scale interact with resource efficiency technologies. The study has important implications for achieving integrated goals of food security, water conservation, and sustainable resource management in semi-arid agricultural regions, while providing empirical evidence for circular economy approaches in food production systems.

KEYWORDS

food security, land consolidation, northern China, precision agriculture, resource use efficiency, smart irrigation, sustainable food systems, water-saving technology

1 Introduction

Global food systems face unprecedented challenges from climate change, resource scarcity, and growing demand. Agricultural water use accounts for over 70% of global freshwater consumption, yet water availability is increasingly constrained by climatic variability and competing demands. In this context, resource-efficient technologies represent critical pathways for reconciling food security with environmental sustainability. Smart irrigation systems offer potential to enhance water productivity while maintaining agricultural output, yet adoption rates remain limited, particularly in developing country contexts. Understanding the structural and institutional factors that enable or constrain technology diffusion is therefore essential for designing effective policies to support sustainable food systems transformation. This study examines how land consolidation and operational scale influence smart irrigation adoption among maize farmers in northern China, a region where water scarcity poses acute constraints on agricultural development.

By analyzing adoption patterns across diverse institutional and environmental contexts, this research contributes insights for promoting resource-efficient technologies in water-stressed agricultural regions.

The urgency of this challenge is underscored by projections that global food demand will increase by 50% by 2050, placing ever greater pressure on agricultural production and resource utilization (Grafton et al., 2015). Agricultural activities currently account for more than 70% of global freshwater consumption (FAO, 2022), yet water availability is increasingly threatened by climate change. Rising temperatures and growing frequency of extreme weather events have resulted in unstable climate patterns and increasingly uneven spatial and temporal distribution of water resources (Yildiz et al., 2022; Intergovernmental Panel On Climate Change (Ipcc), 2023; Saleem et al., 2025), complicating global water management and intensifying tensions between food production and environmental sustainability (Godfray et al., 2010). The international community has recognized these interconnected challenges through the Sustainable Development Goals, particularly SDG 2 (Zero Hunger) and SDG 6 (Clean Water and Sanitation), which call for agricultural innovation that jointly addresses food security and resource conservation (Springmann et al., 2018). Smart irrigation technologies provide a potential means of reconciling these objectives by improving resource-use efficiency while sustaining agricultural productivity, making the adoption and diffusion of such technologies essential for designing sustainable food systems capable of supporting population growth within planetary boundaries (Rockstróm et al., 2017). It is imperative to underscore the importance of precision agriculture, delivered through the convergence of technology, digitization, and innovation, for safeguarding the food security of future generations (Cook et al., 2025; Song and Sun, 2025). The transition to the digital era has catalyzed a profound transformation in farming practices, unlocking unprecedented levels of efficiency and productivity (Baiming and Voskerichyan, 2024). The integration of advanced technologies—artificial intelligence (AI), the Internet of Things (IoT), big-data analytics, robotics, and blockchain—has propelled precision agriculture into a new epoch commonly termed Agriculture 4.0 or smart farming (Kumar Apat et al., 2023).

These global pressures manifest with particular intensity in northern China, a region that illustrates both the promise and complexity of agricultural technology adoption. China plays an essential role in global food security, with a particularly high share of agricultural water use, yet faces mounting pressure to balance food supply with severe constraints of limited water resources and environmental stress (Wang et al., 2017; Altemus Cullen et al., 2025; Lu et al., 2015). The challenges are particularly acute in northern China, where the continued growth of food production has been accompanied by escalating resource depletion and environmental stress, including land degradation and soil erosion (Ash and Edmonds, 1998; Jiao, 2010). Despite significant water limitations, the center of China's agricultural production has been gradually shifting toward this northern region (Jiao, 2010), creating a pressing need for water-efficient farming practices. Northern China is characterized by a semi-arid to arid climate with limited precipitation and strong evaporation; traditional irrigation methods remain inefficient, resulting in significant water loss (Lakhiar et al., 2024) and posing serious challenges to sustainable agricultural development (Zhu et al., 2022). Agricultural systems in this region typically follow a mixed farming and pastoral model with high water demand. Maize, the principal crop in northern China, covers extensive areas and depends heavily on water availability. Under reduced precipitation and intensified evaporation linked to climate change (Su et al., 2022; Wan et al., 2022), improving irrigation practices for maize has become essential to enhance yields and maintain food security (Cao et al., 2021). Increasing irrigation efficiency and reducing water consumption are therefore central to achieving sustainable agricultural development in this region.

Smart irrigation technology has emerged as a modern agricultural innovation capable of addressing these challenges. In response to the interconnected water-food-climate crisis (Behnassi et al., 2024), smart irrigation systems (Gamal et al., 2025; Ndunagu et al., 2022; Khan et al., 2021) enhance water-use efficiency, reduce irrigation losses, and improve agricultural productivity through precision management enabled by sensors, data acquisition, and automated control systems (Ali et al., 2025). These systems continuously monitor soil moisture, climatic variables, and related data to adjust irrigation volumes in real time according to crop requirements, preventing both over-irrigation and under-irrigation and thereby substantially improving the efficiency of water resource utilization (Barkunan et al., 2019; Ismail et al., 2019). Beyond water savings, smart irrigation systems can optimize irrigation scheduling through data-driven analysis, minimize water waste, and reduce dependence on manual labor, thereby lowering labor costs and improving overall agricultural efficiency (Kavianand et al., 2016; Morchid et al., 2025). For large-scale farming operations, such technologies not only decrease labor intensity but also increase irrigation accuracy, contributing to higher yields and improved crop quality (Touil et al., 2022; Ahmed et al., 2023; Jaafar and Kharroubi, 2021). In contrast, traditional irrigation typically relies on manual control or fixed irrigation schedules, which rarely align with dynamic crop water demands and often result in resource waste. The adoption of smart irrigation enables greater precision and automation in agricultural production, particularly in arid and semi-arid areas, thereby enhancing water-use efficiency and crop productivity (Morchid et al., 2024). Smart irrigation systems prioritize sustainability, resilience, and regenerative practices, thereby ushering in a new era of agricultural innovation.

More broadly, the adoption of resource-efficient agricultural technologies represents a critical pathway for sustainable food systems development (Pretty et al., 2018). Smart irrigation systems contribute to sustainability across multiple dimensions: environmentally through water conservation and reduced nutrient leaching, economically through improved crop yields and reduced input costs, and socially through enhanced food security in water-stressed regions (Birkenholtz, 2017). Beyond its technical advantages, smart irrigation aligns with the broader framework of circular economy in agriculture, which emphasizes resource efficiency and waste minimization (Jurgilevich et al., 2016). In water-limited environments, precision irrigation contributes to circular water management by optimizing application rates, reducing runoff, and enhancing nutrient utilization, situating smart irrigation not only as a technological innovation but also as a key element in the transition toward sustainable and resilient food systems (Kalmykova et al., 2018).

Despite these compelling advantages and alignment with sustainable development goals, the practical promotion of smart irrigation remains limited and faces several constraints (Qian et al., 2024; Pagano et al., 2023; Idoje et al., 2021). Despite documented efficiency gains, precision and smart irrigation remain underused in practice, with uptake limited by extension and capability gaps (Timpanaro et al., 2023). Foremost among adoption barriers is the high initial investment cost. Smart irrigation systems require sensors, automated control units, and related infrastructure, all of which involve considerable installation and maintenance expenses; for small and medium-sized farmers with limited capital, the long payback period makes it difficult to afford such investments (Ahmed et al., 2018; Garc-a et al., 2020). Furthermore, although smart irrigation offers clear advantages in water conservation and operational efficiency, many farmers have only limited understanding of its functions and benefits. In the absence of sufficient technical training and support, willingness to adopt the technology remains low (Genius et al., 2014; Koundouri et al., 2006). The dissemination of smart irrigation is also influenced by broader contextual factors, including infrastructure, policy incentives, and market conditions. In remote areas, inadequate communication and power facilities hinder system operation and maintenance, while weak policy frameworks and insufficient subsidies reduce farmers' motivation to invest in these technologies. Due to these factors, the adoption of smart irrigation technology in northern China remains limited (Han et al., 2020; Yan et al., 2020), and the overall diffusion rate has not yet met expectations (Tao et al., 2024; Pivoto et al., 2019). With roughly 84% of the world's farmers being smallholders, the challenge is even more daunting for those operating on a micro scale (Zeng et al., 2025).

These adoption barriers raise a critical question: what structural and institutional conditions might help farmers overcome the cost and information constraints that impede smart irrigation uptake? Land consolidation and large-scale farming have become key trends in agricultural modernization that may provide an answer. Supported by land transfer policies and rural land system reforms, intensive land management is increasingly viewed as a central pathway for improving production efficiency and facilitating technology adoption. Through land consolidation, farmers can address challenges such as fragmented landholdings, limited labor, and capital shortages, thereby enhancing productivity and creating favorable conditions for adopting high-cost technologies such as smart irrigation (Ngango and Hong, 2021). Recent evidence shows that land fragmentation generally constrains uptake of technology-intensive green practices, while resource endowments and organizational integration mitigate these barriers (Das et al., 2025).

Empirical studies indicate that large-scale operations promote the application of new agricultural technologies by providing greater financial capacity, optimizing resource allocation, and strengthening technical support—factors that are particularly relevant for technologies requiring substantial upfront investment (Xie et al., 2017). In large-scale systems, economies of scale help distribute technology costs more efficiently, improving the economic feasibility of smart irrigation. In contrast, small-scale farms, constrained by financial and managerial limitations, often find it difficult to implement such technologies (Dhillon and Moncur, 2023; Kendall et al., 2022). Large-scale operations not only alter production structures but also facilitate the broader adoption of modern agricultural technologies such as soil testing, formula fertilization, and integrated pest management, all of which depend on contiguous land management.

Research on technology adoption in agriculture has increasingly recognized the importance of these institutional arrangements and socioeconomic contexts (Shikuku et al., 2017). Land consolidation and farm scale affect not only the economic viability of technology investments but also farmers' access to information, credit, and technical support. These factors are particularly salient in developing country contexts where fragmented landholdings and limited institutional support constrain sustainable intensification efforts (Lowder et al., 2016). Understanding how land tenure arrangements facilitate or hinder adoption of resource-efficient technologies provides insights for designing policies that promote sustainable agricultural transformation. At the same time, the relationship between farm scale and technology adoption intersects with debates about inclusive development and smallholder participation in sustainable food systems (Wiggins et al., 2010). While large-scale operations may more readily adopt capital-intensive technologies, ensuring smallholder access to resource-efficient innovations remains crucial for equitable sustainability transitions (Maertens and Barrett, 2013). Examining scale effects therefore contributes to understanding pathways for inclusive sustainable intensification.

However, while existing studies have examined the relationship between agricultural scale and technology adoption (Hu et al., 2022), most have focused on regions with concentrated agricultural activity, leaving northern China relatively understudied. This region's fragmented land resources, diverse production systems, and uneven economic development suggest that farmers' technology adoption behaviors may differ substantially from those observed elsewhere. Moreover, the mechanisms linking land consolidation and large-scale operation to farmers' adoption of smart irrigation are complex. Beyond scale effects, factors such as policy support, technological awareness, capital availability, and market demand may also play decisive roles. Although prior research has emphasized the relationship between large-scale farming and technology adoption, few studies have explored in depth how land consolidation and farm scale influence farmers' acceptance of smart irrigation technology across diverse institutional and environmental contexts—precisely the conditions that characterize northern China's maize-producing regions.

This study addresses these gaps by investigating the adoption of smart irrigation systems among maize farmers in northern China, examining the roles of land consolidation and large-scale operation within the broader context of sustainable agricultural development. Specifically, this research aims to: (1) analyze the impact of land consolidation and operational scale on smart irrigation technology adoption using household survey data from 803 maize farmers in Inner Mongolia; (2) examine how these effects vary by institutional support mechanisms, regional suitability, and water resource endowment through heterogeneity analysis;

(3) contribute to literature on sustainable food systems by revealing how land tenure arrangements and farm scale interact with resource efficiency technologies; and (4) provide empirical evidence for policy design aimed at improving water efficiency, promoting agricultural modernization, and advancing circular economy approaches in food production systems.

Under the dual pressures of food security and water scarcity, understanding how maize growers in northern China adopt smart irrigation technology and how this process is shaped by land consolidation and large-scale operation constitutes the central focus of this study. Addressing this issue will clarify the relationship between institutional innovation, scale expansion, and technological advancement. It will also provide micro-level evidence to inform policies aimed at achieving integrated goals of food security, water conservation, and sustainable resource management in semi-arid agricultural regions, while offering empirical insights for agricultural technology promotion in comparable settings worldwide.

2 Theoretical model and research hypotheses

This study develops a theoretical model based on expected profit maximization to examine the impact of land consolidation and large-scale operation on the adoption of smart irrigation technology (Foster and Rosenzweig, 2010). The framework posits that land consolidation improves the average comprehensive output rate of land, though it may have negative effects on returns to scale in grain production.

We assume that, given resource constraints, a farmer's decision to adopt smart irrigation technology results from a dynamic comparison of costs and benefits, with the objective of maximizing profits. The farmer's technology decision can be expressed as the following dynamic optimization model:

$$\max_{x\in[0,1]} \sum_{t=0}^{\bar{r}} \beta^t \pi_t \tag{1}$$

Here, β represents the discount rate, and x denotes the farmer's decision on whether to adopt smart irrigation technology. When $x = 0$, the farmer continues to use the traditional irrigation method, with the profit obtained being $\pi_t = \pi_u$. When $x = 1$, the farmer abandons the previous irrigation method in favor of adopting smart irrigation technology, with the profit obtained being $\pi_t = \pi_c$.

The value function V_{π_G} that satisfies the Bellman equation can be expressed as:

$$V_{\pi_G} = \max_{x\in\{0,1\}} \{\pi_G - C, \pi_U + \beta \int_0^B v_{\pi_G}{}' dF_{\pi_G}{}'\} \tag{2}$$

Here, C represents the total cost of technology transition, that is, the corresponding investment made in adopting smart irrigation technology. Define π_{GE} as a critical value, which represents an equilibrium profit level after adopting smart irrigation technology. At this profit level, the profits corresponding to the two different decisions of adopting and not adopting smart irrigation technology are equal. Therefore, the value of π_{GE} can be calculated as follows:

$$\pi_{GE} = (1-\beta)C(L) + \pi_U + \beta \int_0^B v_{\pi'_G} dF_{\pi'_G} \tag{3}$$

At this stage, the farmer's decision regarding the adoption of smart irrigation technology can be expressed as follows:

$$x = \begin{cases} 0 & \text{if } \pi_G \le \pi_{GE} \\ 1 & \text{if } \pi_G > \pi_{GE} \end{cases} \tag{4}$$

If the profit π_G obtained after adopting smart irrigation technology is less than or equal to the critical value π_{GE}, the farmer will choose to maintain the status quo and not adopt the technology. Conversely, if π_G exceeds π_{GE}, the farmer will adopt smart irrigation technology.

Further, the total cost of technology transition C can be defined as:

$$C = c(L) \times L \tag{5}$$

where $c(L)$ represents the unit cost of technology transition, and L denotes the scale of operation. Based on the derivation above, the relationship between the critical profit level and the operational scale can be expressed as:

$$\frac{\partial \pi_{GE}}{\partial L} = (1-\beta) \times \frac{\partial C}{\partial L} \tag{6}$$

The sign of $\frac{\partial \pi_{GE}}{\partial L}$ is thus the same as that of $\frac{\partial C}{\partial L}$. If the unit cost of adopting smart irrigation technology decreases as the operational scale increases, and the rate of reduction in unit cost exceeds the rate of scale expansion, then the total cost of technology transition will also decline. Consequently, the equilibrium value π_{GE} decreases with increasing L, expressed as:

$$\frac{\partial C}{\partial L} < 0 \Rightarrow \frac{\partial \pi_{GE}}{\partial L} < 0 \tag{7}$$

Following the expansion of land operation scale, farmers can achieve economies of scale when purchasing smart irrigation equipment, which reduces unit costs (Figure 1). For instance, large-scale farmers can purchase equipment in bulk and benefit from more favorable prices. In addition, land consolidation reduces plot fragmentation, thereby lowering installation costs per unit area as consolidation increases. This relationship can be expressed as $\frac{\partial c(L)}{\partial L} < 0$.

On this basis, since the unit cost decreases with the increase in the scale of operation, and the degree of unit cost reduction is greater than the degree of scale expansion, the total cost of technology transition will also decrease. That is, $\partial C/\partial L < 0$.

Given that the unit cost decreases with the scale of operation and that the reduction rate surpasses the expansion rate, the total technology transition cost declines ($\frac{\partial C}{\partial L} < 0$). According to the model derivation, a reduction in C with increasing L results in a lower critical profit level ($\frac{\partial \pi_{GE}}{\partial L} < 0$). A lower π_{GE} raises the probability that $\pi_G > \pi_{GE}$, meaning that farmers are more likely to find the adoption of smart irrigation technology economically feasible (Blasch et al., 2022).

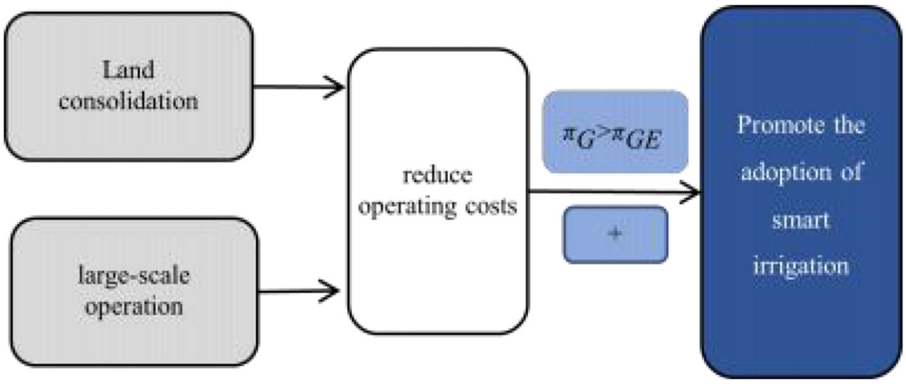

FIGURE 1
The mechanism on the impactof land consolidation and large-scale operation on the adoption of smart irrigation technology.

Therefore, as land consolidation and large-scale operation expand, the adoption threshold for smart irrigation technology decreases. Farmers perceive adoption as more cost-effective and are thus more inclined to implement it, leading to a higher probability of adoption.

Based on this theoretical framework, the following hypotheses are proposed:

H1: Land consolidation positively influences the adoption of smart irrigation technology.
H2: Large-scale operation positively influences the adoption of smart irrigation technology.

3 Empirical model

In studying farmers' production technology adoption behavior, whether a household adopts smart irrigation technology is treated as a binary variable. Accordingly, this study employs a binary Logit regression model for empirical analysis. The basic regression model is specified as follows:

$$\text{Adoption} = \alpha \cdot \text{consolidation} + \beta \cdot \text{farmsize} + \delta X + \epsilon \qquad (8)$$

In Equation 8, Adoption is the unobservable latent variable; consolidation denotes land consolidation; farmsize represents large-scale operation; X is a vector of control variables listed in Table 1; α, β, and δ are parameters to be estimated; and ϵ is the disturbance term, which follows a standard normal distribution.

The empirical analysis proceeded through three main stages. First, a baseline Logit regression was conducted to evaluate the effects of land consolidation and large-scale operation on the adoption of smart irrigation technology. The Logit model was selected because the dependent variable is binary (adoption versus non-adoption). This baseline estimation provided an initial understanding of the key relationships among the variables.

Second, a series of robustness checks were performed to validate the stability of the results. To address potential information loss from the binary outcome and to capture the intensity of adoption, the dependent variable was replaced with the actual number of smart irrigation devices owned by each household. The model was then re-estimated using Ordinary Least Squares (OLS) regression, allowing for a more detailed assessment of how land consolidation and large-scale operation influence the degree of adoption. To control for intra-village correlation, robust standard errors were clustered at the village level, ensuring that standard errors were not underestimated and that the significance tests remained reliable. To reduce the effect of extreme values, the core explanatory variables-corn planting area, per capita corn planting area, and average corn planting area per plot-were subjected to 1% Winsorization. This process truncated the top and bottom 1% of data, minimizing the influence of outliers. The Logit model was then re-estimated using these adjusted variables to confirm the robustness of the findings.

Third, heterogeneity analysis was performed to examine differential effects of land consolidation and large-scale operation across varying conditions.

a) The sample was divided based on whether water-saving irrigation technology had been promoted by the government. Separate regressions were estimated for these groups to assess the influence of policy intervention on adoption behavior. The results showed that government promotion significantly increases adoption rates, particularly among large-scale farmers.
b) The sample was further classified according to regional suitability for corn cultivation, distinguishing between high-suitability and medium-to-low-suitability areas. The findings indicated that the impacts of land consolidation and large-scale operation are more pronounced in medium-to-low-suitability areas, underscoring the role of regional natural endowments.
c) Finally, the sample was split based on village location within or outside the Yellow River irrigation area. Results revealed that farmers in non-Yellow River areas, where water resources are more limited, demonstrated a stronger willingness to adopt smart irrigation technology. This outcome highlights

TABLE 1 Variable definitions and descriptive statistics.

Variable type	Variable name	Definition and values	Mean	Standard deviation
Dependent variable	Adoption of smart irrigation technology	Whether irrigation is equipped with smart devices (0 = Not Adopted, 1 = Adopted)	0.31	0.46
	Intensity of smart irrigation technology adoption	Number of smart devices installed by the household	0.37	0.68
Core explanatory variables	Land consolidation	Average corn planting area per plot (hectares/plot)	2.18	2.38
	Large-scale operation	Corn planting area (hectares)	6.93	9.40
		Per capita corn planting area (hectares/person)	2.08	2.64
Farmer individual characteristics	Gender	0 = Female, 1 = Male	0.96	0.19
	Age	Age of the household head at the time of the survey (years)	53.07	9.36
	Health status	Health of household head (1 = Very Healthy... 5 = Very Unhealthy)	1.32	0.68
	Marital status	Household head is married = 1 otherwise = 0	0.98	0.16
	Village cadre	Household head is a village cadre or group leader (0 = No, 1 = Yes)	0.17	0.37
Household characteristics	Family size	Number of family members (persons)	3.68	1.44
	Family income level	Logarithm of per capita total family income (yuan)	10.72	1.44
	Non-agricultural employment	Family has non-agricultural employment (0 = No, 1 = Yes)	0.31	0.46
	Agricultural technology training	Family has participated in technical training (0 = No, 1 = Yes)	0.40	0.49
Village characteristics	Natural Disasters	Village experienced disasters in past ten years (1 = Yes, 0 = No)	0.83	0.37
	Irrigation conditions	Village has surface-water (river) irrigation (1 = Yes, 0 = No)	0.13	0.34
	Transportation conditions	Distance to the nearest highway (kilometers)	31.60	27.15

the importance of water resource endowment in influencing technology adoption behavior.

4 Data sources and descriptive statistics

4.1 Data sources

The data used in this study originate from the Agricultural and Rural Modernization Surveys (ARMS) conducted in 2022 by the Institute of Macro-Agriculture and the College of Economics and Management at Huazhong Agricultural University, in collaboration with the College of Economics and Management at Inner Mongolia Agricultural University. The surveys were implemented in Otog Front Banner (Eerduosi City) and Urad Front Banner (Bayannur City) within the Inner Mongolia Autonomous Region. A combination of stratified and random sampling methods was employed.

At the township level, 11 townships or soums located in major agricultural areas were selected according to the production structure of county-level primary industries. At the village level, 130 sample villages were randomly chosen using indicators such as population, land area, and economic development. At the household level, approximately 10 farming households were randomly selected from each village's list of agricultural producers for questionnaire interviews. In total, the survey covered 130 villages and more than 1,300 households. After excluding samples with missing or extreme values related to drip-irrigation technology, 803 valid samples were retained for analysis.

Household questionnaires were administered through one-on-one interviews with household heads or other family members primarily responsible for production and management decisions. The questionnaire covered family demographics, labor status, agricultural production and management conditions, and farmers' cognition, willingness, and behavior concerning smart-irrigation technology. The village-level questionnaire was conducted with village heads, party branch secretaries, or other knowledgeable local officials. It collected information on population, land and water resources, infrastructure, agricultural technology extension, production conditions, and relevant local policies.

4.2 Variable settings and descriptive statistics

4.2.1 Dependent variable

Adoption of smart-irrigation technology. Adoption is defined as the use of smart-irrigation equipment (Ndunagu et al., 2022)—including automatic fertigation machines, automatic back-flushing disc filters, fertilizer buckets, remote-controlled valves (electromagnetic valves and controllers), soil-moisture meters, and field meteorological monitoring stations—on the basis of traditional drip irrigation. If any of these devices are used, the household is considered an adopter; otherwise, it is classified as a non-adopter. The intensity of smart-irrigation adoption is measured by the number of such devices owned by the household.

4.2.2 Core explanatory variables

Land Consolidation and Large-Scale Operation. The degree of land consolidation is measured by the average plot size. Large-scale operation is measured by total corn-planting area and per-capita corn-planting area.

4.2.3 Control variables

To minimize potential estimation bias arising from omitted variables, the model includes multiple controls drawn from relevant literature (Serote et al., 2021; Zakaria et al., 2020; Jaafar and Kharroubi, 2021; YATRIBI, 2020) and theoretical considerations. These variables capture three dimensions: individual farmer characteristics, household management characteristics, and external environmental conditions.

1. Individual characteristics: Age, gender, and health status of the household head are included to represent human-capital endowment, given the household head's decisive role in production decisions.
2. Household characteristics: Family size, per-capita family income, non-agricultural employment, and participation in agricultural-technology training reflect managerial resources and economic capacity. Because income distribution varies considerably across farm sizes, per-capita family income will be log-transformed in the empirical analysis to mitigate the effect of extreme values.
3. External environment: To capture the influence of natural and infrastructural factors, three village-level variables—natural disasters, irrigation conditions, and transportation convenience—are included. These variables reflect climate risk, water-resource availability, and accessibility, respectively.

To make the core findings more intuitive, the following visualization strategy is adopted: point estimates with confidence interval bar charts (coefplot), which highlights the direction and significance. Specifically, we have plotted the marginal effects of three key explanatory variables—Corn planting area, Per capita corn planting area, and Average corn planting area per plot—on the probability of adopting smart irrigation technology.

Figure 2 shows the marginal effects of these variables and their 95% confidence intervals. As can be seen from the figure, the marginal effects of per capita corn planting area and average corn planting area per plot on the adoption of smart irrigation technology are relatively significant, with similar effect sizes, both around 1.4 percentage points. This indicates that as per capita planting area or average planting area per plot increases, the probability of farmers adopting smart irrigation technology significantly rises. The marginal effect of average corn planting area per plot is relatively smaller, at approximately 0.4 percentage points, but it remains statistically significant.

We believe that these visualization results not only intuitively display the direction and significance of the key variables' impacts but also provide deeper insights into how land consolidation and large-scale planting affect the adoption of smart irrigation technology, helping to grasp the core findings of our study more quickly.

5 Empirical results and analysis

5.1 Impact of land consolidation and large-scale operation on farmers' adoption of smart irrigation technology

This study examines the effects of land consolidation and large-scale operation on farmers' adoption of smart-irrigation technology using Stata 17.0 for statistical analysis in Table 2. The dependent variable is the adoption of smart-irrigation technology, and the core explanatory variables are land consolidation and large-scale operation. Separate Logit regressions were estimated for each specification. All models include county-level fixed effects. The Pseudo R2 values range from 0.0275 to 0.0328, and the LR chi^2 statistics are significant at the 5 percent level, indicating an acceptable model fit.

The regression results demonstrate that all three measures of scale and consolidation exert a positive and statistically significant influence on the adoption of smart-irrigation technology at the 5 percent level or higher. These findings confirm the proposed logical relationship of "land consolidation → large-scale operation → technology adoption."

Specifically:

When the average corn-planting area per plot (hectares per plot) is used to measure land consolidation, the estimated coefficient is 0.0650 and significant at the 5 percent level (column 1). This indicates that plot-level consolidation—by reducing land fragmentation—facilitates technology adoption, reinforcing the results obtained under other specifications.

When total corn-planting area (hectares) is used to represent operational scale, the coefficient is 0.0204 and significant at the 5 percent level (column 2). This implies that, holding other factors constant, each additional hectare of corn-planting area increases the log-odds of adopting smart-irrigation technology by approximately 2.1 percent. Expansion in cultivated area enables farmers to realize economies of scale, lowering the per-unit cost of adoption and encouraging the use of smart-irrigation systems.

When per-capita corn-planting area (hectares per person) is employed as the measure of scale, the coefficient rises to 0.0661 and becomes significant at the 1 percent level (column 3). Because this indicator adjusts for differences in household labor, the result suggests that the observed scale effect arises primarily from expanded operational area rather than labor input alone.

Overall, land consolidation and large-scale operation both contribute to spreading the fixed costs of smart-irrigation equipment, lowering the investment threshold per unit area, and enhancing expected profits. These mechanisms jointly motivate farmers to adopt smart-irrigation technology, thereby validating the study's research hypotheses.

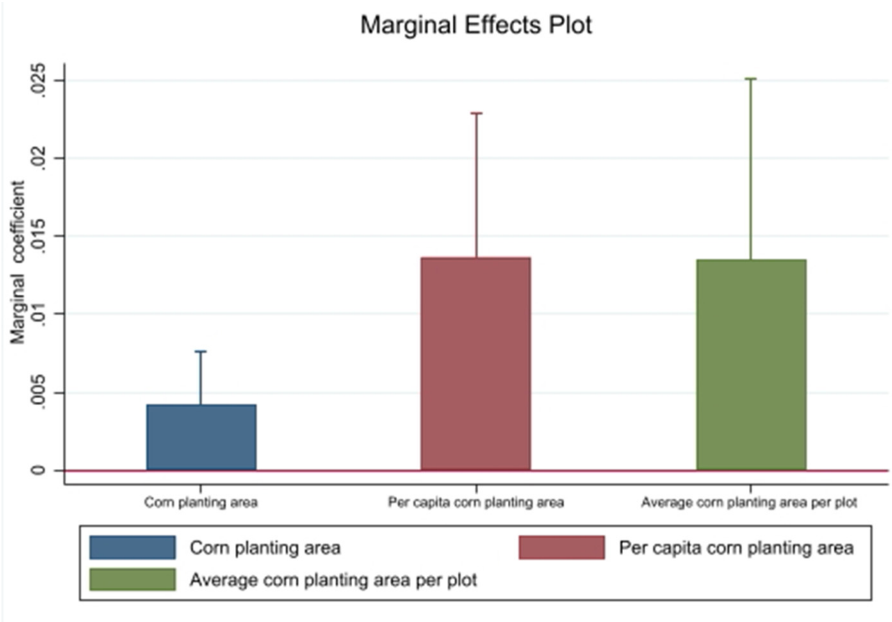

FIGURE 2
The marginal effects plot on the impact of land consolidation and large-scale operation on the adoption of smart irrigation technology.

5.2 Robustness analysis

5.2.1 Robustness test 1: replacing the dependent variable

To mitigate potential information loss arising from the binary measurement of "whether to adopt" and to further verify the effects of land consolidation and operational scale on the extent of smart-irrigation technology adoption, this study replaces the dependent variable with the number of smart-irrigation devices installed by each household and re-estimates the model using Ordinary Least Squares (OLS). The results are presented in Table 3.

5.2.1.1 Model fit and significance

The adjusted R2 values for all specifications are relatively low (0.0118–0.0138), suggesting that although the impact of corn-planting area is statistically significant, other unobserved factors may also influence the number of devices adopted. The modest explanatory power indicates that while the model captures key relationships, there remains scope for improvement through additional variables or alternative model forms.

5.2.1.2 Robustness of core explanatory variables

The coefficients of the main explanatory variables remain positive and significant across all specifications. Specifically, for every additional hectare of average corn-planting area per plot, the number of installed devices increases by 1.99 units; for every additional hectare of total corn-planting area, the number increases by 0.18 units; and for every additional hectare of per-capita corn-planting area, the number increases by 0.94 units. These results indicate that the greater the degree of land consolidation, total scale, or per-capita scale of operation, the more farmers tend to adopt multiple sets of smart-irrigation devices to enable precise management over larger cultivated areas.

After replacing the dependent variable with a continuous measure and standardizing the scale indicators in hectares, the positive and significant influence of land consolidation on

TABLE 2 Impact of land consolidation and large-scale operation on farmers' adoption of smart irrigation technology (Logit).

Variable	Adoption of smart irrigation technology		
	(1)	(2)	(3)
Average corn planting area per plot (hectares/plot)	0.0650** (0.0289)		
Corn planting area		0.0204** (0.0086)	
Per capita corn planting area (hectares/person)			0.0661*** (0.0231)
Farmer individual characteristics	Controlled	Controlled	Controlled
Household characteristics	Controlled	Controlled	Controlled
Village characteristics	Controlled	Controlled	Controlled
County-level fixed effects	Controlled	Controlled	Controlled
Constant	−0.9236	−1.0649	−1.6034
	(1.2886)	(1.2718)	(1.3609)
Number of observations	803	803	803
Log likelihood	−483.2037	−483.7037	−485.8162
LR $chi^2(14)$	26.2311**	26.6774**	24.2394**
Pseudo R2	0.0328	0.0318	0.0275

Robust standard errors in parentheses. $^{**}p < 0.05$, $^{***}p < 0.01$.

TABLE 3 Impact of land consolidation and large-scale operation on the intensity of smart-irrigation technology adoption (OLS Model).

Variable	Number of smart devices installed for irrigation by the farm household		
	(1)	(2)	(3)
Average corn planting area per plot (hectares/plot)	0.0199** (0.0081)		
Corn planting area		0.0018** (0.0008)	
Per capita corn planting area (hectares/person)			0.0094** (0.0038)
Farmer individual characteristics	Controlled	Controlled	Controlled
Household characteristics	Controlled	Controlled	Controlled
Village characteristics	Controlled	Controlled	Controlled
County-level fixed effects	Controlled	Controlled	Controlled
Constant	0.2661	0.3076	0.2297
	(0.3264)	(0.3223)	(0.3215)
Number of observations	803	803	803
Adjusted R2	0.0118	0.0138	0.0136

Robust standard errors in parentheses. ** $p < 0.05$.

TABLE 4 Robustness test 2—replacing clustered standard errors (village level).

Variable	Adoption of smart irrigation technology		
	(1)	(2)	(3)
Average corn planting area per plot (hectares/plot)	0.0650** (0.0298)		
Corn planting area		0.0204*** (0.0072)	
Per capita corn planting area (hectares/person)			0.0661*** (0.0217)
Farmer individual characteristics	Controlled	Controlled	Controlled
Household characteristics	Controlled	Controlled	Controlled
Village characteristics	Controlled	Controlled	Controlled
County-level fixed effects	Controlled	Controlled	Controlled
Constant	−0.9236	−1.0649	−1.6034
	(1.3032)	(1.3020)	(1.4066)
Number of observations	803	803	803
Log likelihood	−483.2037	−483.7037	−485.8162
LR chi^2(14)	33.8713***	33.7821***	32.0414***
Pseudo R2	0.0328	0.0318	0.0275

Standard errors in parentheses are clustered at the village level. ** $p < 0.05$, *** $p < 0.01$.

the number of smart-irrigation devices remains robust. This finding confirms that the theoretical mechanism proposed for adoption decisions also applies to the depth or intensity of technology adoption.

5.2.2 Robustness test 2: replacing clustered standard errors

To address potential intra-village correlation that might bias the estimation of standard errors, this study re-estimates the baseline Logit model using robust standard errors clustered at the village level. The results are reported in Table 4.

5.2.2.1 Model fit and significance

The Pseudo R2 values of all models remain relatively low (0.0275–0.0328), suggesting that although the effect of corn-planting area is statistically significant, additional unobserved factors may influence adoption behavior. This limited explanatory power indicates that, while the model effectively captures key relationships, further refinements could improve its performance.

5.2.2.2 Significance and stability of the core explanatory variables

After clustering at the village level, the coefficients of the main explanatory variables remain positive and significant, confirming the robustness of the findings. Specifically, the coefficient for average corn-planting area per plot remains 0.0650, with its standard error increasing slightly from 0.0289 to 0.0298, and significance maintained at the 5 percent level. The coefficient for total corn-planting area remains 0.0204, while the standard error decreases from 0.0086 to 0.0072, increasing the significance from 5 percent to 1 percent. The coefficient for per-capita corn-planting area (hectares per person) remains 0.0661 and significant at the 1 percent level.

5.2.2.3 Interpretation

The positive and significant influence of land consolidation and operational scale on smart-irrigation adoption persists after clustering, and the significance of the core variables is even stronger. These results indicate that the initial estimates were not inflated by unaccounted village-level correlation. Consequently, the research hypotheses are further validated, and the robustness of the main conclusions is confirmed.

5.2.3 Robustness test 3: winsorizing core explanatory variables at the 1st and 99th percentiles

To reduce the potential influence of extreme values on the estimation results, this study applies a 1% Winsorization to continuous variables such as total family income and scale of operation. In addition, a 1% upper and lower quantile truncation is performed on the core explanatory variables—average corn-planting area per plot, total corn-planting area, and per-capita corn-planting area and the Logit model is re-estimated.

5.2.3.1 Model fit and significance

The model fit remains close to that of the baseline regression, with Pseudo R^2 values ranging from 0.0256 to 0.0271 (compared with 0.0275 to 0.0328 in the baseline model), and the LR chi^2 statistics remain significant at the 5 percent level. These results indicate a stable and well-specified model. Table 5 presents the

TABLE 5 Robustness test 3—winsorizing core explanatory variables.

Variable	Adoption of smart irrigation technology		
	(1)	(2)	(3)
Average corn planting area per plot (hectares/plot)	0.0856** (0.0407)		
Corn planting area		0.0245** (0.0105)	
Per capita corn planting area (hectares/person)			0.0773** (0.0380)
Farmer individual characteristics	Controlled	Controlled	Controlled
Household characteristics	Controlled	Controlled	Controlled
Village characteristics	Controlled	Controlled	Controlled
County-level fixed effects	Controlled	Controlled	Controlled
Constant	−1.1787	−1.4176	−1.6456
	(1.2990)	(1.2961)	(1.3648)
Number of observations	803	803	803
Log likelihood	−486.0146	−486.7858	−486.5322
LR chi^2(14)	25.0724**	23.7255**	24.4950**
Pseudo R2	0.0271	0.0256	0.0261

Robust standard errors in parentheses. $^{**}p < 0.05$.

estimation results after Winsorization, which are highly consistent with the baseline findings.

5.2.3.2 Coefficient comparison and interpretation

After controlling for extreme values, the coefficients of the core explanatory variables remain positive and statistically significant, with slightly larger magnitudes than in the baseline regression. Specifically, the coefficient for average corn-planting area per plot increases from 0.0650 to 0.0856, suggesting that, after removing extremely fragmented plots, the effect of land consolidation on technology adoption becomes more evident. The coefficient for total corn-planting area increases from 0.0204 to 0.0245, indicating that the earlier results were not driven by a few exceptionally large-scale farms. The coefficient for per-capita corn-planting area rises from 0.0661 to 0.0773, further confirming the robustness of the scale effect even after adjusting for household labor differences.

5.2.3.3 Overall interpretation

The significance and economic implications of the core explanatory variables remain stable following Winsorization. These results demonstrate that the observed positive impact of land consolidation and large-scale operation on the adoption of smart-irrigation technology is not driven by extreme observations. Therefore, the research hypotheses continue to hold after controlling for the influence of outliers.

5.2.4 Robustness test 4: estimation results based on the instrumental variable approach

In the robustness test section of the paper, we paid special attention to mitigating endogeneity issues. Drawing on relevant research methods, this study considers multiple characteristics in the production behavior of farmers' adoption of new technologies, such as education level, land size, non-agricultural income, family structure, and gender. These characteristics not only reflect the economic status and production capacity of farmers but also may influence their willingness and ability to adopt new technologies. However, when these characteristics become particularly important in a certain region, farmers in other regions with the same characteristics may still be subject to different considerations in technology adoption. The two-stage least squares (2SLS) method is employed to address the endogeneity problem.

To ensure the relevance and exogeneity of the instrumental variables, first, in terms of relevance, these variables were selected based on their theoretical association with the explanatory variables (Wooldridge, 2015). We calculated the Average corn planting area per plot (hectares/plot), Corn planting area, and Per capita corn planting area (hectares/person) for the sample of farmers in the village. Then, excluding the individual farmer's own sample, we computed the mean values of the corresponding indicators for the village sample. This step helps us construct instrumental variables that are independent of specific farmers, thereby enhancing the exogeneity of the model. Second, in terms of exogeneity, the selection of these instrumental variables is based on their correlation with the dependent variable (adoption of smart irrigation technology) while being uncorrelated with the model error term. Specifically, these instrumental variables capture the characteristics of agricultural activities at the village level, which are distinct from the micro-level farmer variables. These characteristics are unlikely to directly influence individual farmers' adoption decisions, thus meeting the exogeneity principle of instrumental variables.

Table 6 reports the 2SLS regression results using these variables as instrumental variables. First, the F-values from the first-stage regression (as shown in the table) are all greater than the conventional critical value of 10, indicating no weak instrumental variable problem. Second, the Kleibergen-Paap rk LM statistic is significant at the 1% level, rejecting the null hypothesis of "under-identification of instrumental variables." These tests demonstrate that the instrumental variables constructed in this paper are reasonable.

In the second-stage regression results, the estimated coefficient for the adoption of smart irrigation technology is significantly positive. This indicates that after controlling for potential endogeneity using instrumental variables, the positive impact of average plot size, corn planting area, and per capita planting area on the adoption of smart irrigation technology remains significant. This suggests that the conclusions drawn earlier still hold after overcoming the potential endogeneity issues in the model.

5.3 Mechanism analysis

As analyzed earlier, land consolidation and large-scale operation do indeed significantly promote farmers' adoption of smart irrigation technology. However, the specific mechanisms through which land consolidation and large-scale operation affect

TABLE 6 Robustness test 4—estimation results based on the instrumental variable approach.

Variable	First stage Average corn planting area	Second stage Adoption of smart irrigation technology	First stage Corn planting area	Second stage Adoption of smart irrigation technology	First stage Per capita corn planting area	Second stage Adoption of smart irrigation technology
Average corn planting area per plot (excluding the household's own plot) at the village level (hectares/plot)	0.486*** (0.102)					
Average corn planting area per plot (hectares/plot)		0.194* (0.108)				
Corn planting area (excluding the household's own) at the village level			0.646*** (6.28)			
Corn planting area				0.038** (2.24)		
Per capita corn planting area (excluding the household's own) at the village level					0.496*** (0.088)	
Per capita corn planting area						0.165** (0.072)
Farmer individual characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Household characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Village characteristics	Yes	Yes	Yes	Yes	Yes	Yes
County-level fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	803	803	803	803	803	803
Kleibergen-Paap rk LM	22.20		39.44		31.44	
Kleibergen-Paap Wald F	22.00		39.20		31.20	

The Kleibergen-Paap rk Wald F statistic exceeds the 10% critical value of 16.38 for weak-instrument identification in the Stock-Yogo test, rejecting the null hypothesis of weak instruments; the Kleibergen-Paap rk LM statistic is significant at the 1% level, rejecting the null hypothesis that the instruments are unidentified. Robust standard errors in parentheses. *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

farmers' adoption behavior of smart irrigation technology still need further verification.

As pointed out earlier, land consolidation and large-scale operation enable farmers to achieve economies of scale when purchasing smart irrigation equipment, and the reduction in unit costs promotes the adoption of smart irrigation technology by farmers.

The results in Table 7 show that the average plot size, corn planting area, and per capita corn planting area have a significant negative impact on the total cost of adopting smart irrigation technology. This means that land consolidation and large-scale operation can reduce the total cost of adopting smart irrigation technology by farmers, which verifies the existence of the cost control impact mechanism.

5.4 Heterogeneity analysis

5.4.1 Heterogeneity analysis 1: government promotion of water-saving irrigation technology

To examine whether government promotion influences the adoption of smart-irrigation technology, this study divides the sample according to whether water-saving irrigation technology has been promoted by the government. Separate regressions are then conducted for the two groups. The estimation results are presented in Table 8.

Government promotion significantly enhances farmers' adoption of smart-irrigation technology, particularly among those operating at larger scales of land consolidation and cultivation. Government support reduces the barriers and risks associated with adopting new technologies, thereby facilitating broader dissemination. This effect is also evident when measured by average corn-planting area per plot, where the coefficients remain positive and significant in the government-promoted sample but weaken or become insignificant in the non-promoted group.

The results suggest that larger-scale farming households have stronger demands for irrigation efficiency and effective water-resource utilization. Government promotion provides these farmers with both the technical support and the institutional assurance required to adopt smart-irrigation systems. Moreover, comparisons of Log Likelihood and Pseudo R2 values indicate that model fit is better in the government-promoted sample than in the non-promoted sample, underscoring the pivotal role of policy intervention in facilitating technology adoption.

TABLE 7 Impact of land consolidation and large-scale operation on the cost of smart irrigation devices (yuan).

Variable	The cost of smart irrigation devices (yuan)		
	(1)	(2)	(3)
Average corn planting area per plot (hectares/plot)	−0.0249** (0.0116)		
Corn planting area		−0.0015** (0.0007)	
Per capita corn planting area (hectares/person)			−0.0084* (0.0048)
Farmer individual characteristics	Yes	Yes	Yes
Household characteristics	Yes	Yes	Yes
Village characteristics	Yes	Yes	Yes
County-level fixed effects	Yes	Yes	Yes
Constant	8.6070***	8.6334***	8.5780***
	(0.4321)	(0.4448)	(0.4409)
Number of observations	783	783	783
Adjusted R2	0.031	0.024	0.026

Robust Standard errors in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

5.4.2 Heterogeneity analysis 2: regional corn suitability levels

To examine how regional natural endowments influence farmers' adoption of smart-irrigation technology, the sample is divided into high-suitability areas and medium-low-suitability areas based on corn-planting suitability levels. The "regional suitability" indicator is built on the Ministry of Agriculture and Rural Affairs' National Planning for Maize Advantage Zones (2008–2015) and the Climatic Zonation of Maize Suitability in Inner Mongolia Autonomous Region. These sources integrate key biophysical factors—climate (≥2,550 °C accumulated temperature), soil type, topography, and water availability—to classify the study area into different maize-suitability levels. In our sample, 491 farm households are located in six townships classified as highly suitable, while 312 households are in five townships of medium–low suitability. Separate regressions are then performed for each group. The estimation results are summarized in Table 9.

5.4.2.1 Model fit and overall findings

All regressions control for individual, household, and village characteristics, as well as county-level fixed effects. The Pseudo R2 values in the medium-low-suitability areas (ranging from 0.0788 to 0.0887) are notably higher than those in the high-suitability areas (approximately 0.03), indicating that the explanatory power of farm-scale factors is stronger in regions with less favorable natural conditions.

5.4.2.2 Interpretation of results

In high-suitability areas, where land and water resources are more abundant, farmers' dependence on advanced irrigation technologies is lower, and the effect of scale variables on adoption is not statistically significant. In contrast, in medium-low-suitability areas, limited land and water resources heighten production constraints. As a result, large-scale operations in these areas create stronger incentives for farmers to adopt water-saving and yield-enhancing technologies such as smart irrigation. These findings highlight that the drivers of technology adoption vary with local natural endowments.

5.4.2.3 Policy implications

From a policy perspective, the results suggest the need for differentiated promotion strategies that consider regional resource endowments. In particular, medium-low-suitability areas should receive greater policy and financial support to enhance the role of smart-irrigation technology in maintaining agricultural stability and improving resource efficiency.

5.4.3 Heterogeneity analysis 3: location within the yellow river irrigation area

To further examine how regional water-resource endowment affects farmers' adoption of smart-irrigation technology, we exploit the fact that the sample sits in the upper Yellow-River basin. We create a dummy equal to 1 if the respondent's village has access to surface-water irrigation (Yellow-River irrigation district) and 0 otherwise. This proxy is drawn directly from the village-level survey question "Does the village have surface-water irrigation?" Of the 803 observations, 107 are within the Yellow-River irrigation district and 696 are outside. Thus, the sample is divided according to whether villages are located inside or outside the Yellow River Irrigation Area (YRIA). Separate regressions are then conducted for each group, with results summarized in Table 10. All regressions control for individual, household, and village characteristics, as well as county-level fixed effects.

5.4.3.1 Model fit and comparison

The sample size is larger in non-YRIA regions, where the estimation results are more stable and the explanatory power of scale variables is stronger. Both per-capita and per-plot land-scale indicators show significant positive effects in these areas. In contrast, although the Pseudo R2 values for YRIA models are relatively higher (approximately 0.147), the coefficients of scale variables are insignificant. This pattern suggests that in regions with abundant water resources, the marginal benefits of expanding operational scale on smart-irrigation adoption are diminished.

5.4.3.2 Interpretation

The findings indicate that regional differences in water-resource endowment play a decisive role in shaping adoption behavior. In the YRIA, where water supply is relatively secure, farmers' dependence on smart-irrigation technology is lower, and scale expansion does not translate into a stronger motivation to adopt. Conversely, in non-YRIA areas characterized by limited water availability, large-scale farming increases water-use pressure, thereby intensifying demand for efficient irrigation technologies and significantly promoting adoption.

These results underscore the need for differentiated policy approaches. In the YRIA, policy efforts should focus on improving technological efficiency and management performance of existing systems. In non-YRIA regions, greater policy and financial support should be directed toward integrating large-scale farming with

TABLE 8 Heterogeneity analysis 1—government promotion of water-saving irrigation technology.

Variable	Adoption of smart irrigation technology					
	(1)	(2)	(3)	(4)	(5)	(6)
	Yes	No	Yes	No	Yes	No
Average corn planting area per plot (hectares/plot)	0.1641*** (0.0613)	0.0171 (0.0348)				
Corn planting area			0.0234** (0.0168)	0.0197 (0.0112)		
Per capita corn planting area (hectares/person)					0.0783*** (0.0277)	0.0518 (0.0386)
Farmer individual characteristics	Controlled	Controlled	Controlled	Controlled	Controlled	Controlled
Household characteristics	Controlled	Controlled	Controlled	Controlled	Controlled	Controlled
Village characteristics	Controlled	Controlled	Controlled	Controlled	Controlled	Controlled
County-level fixed effects	Controlled	Controlled	Controlled	Controlled	Controlled	Controlled
Constant	2.0594	−2.6813*	−2.8156*	1.7123	1.5611	−3.5814**
	(1.7929)	(1.6276)	(1.7910)	(1.6068)	(1.8065)	(1.6423)
Number of observations	401	395	401	395	401	395
Log likelihood	−233.2217	−238.9669	−234.0850	−238.9246	−231.7908	−240.3514
LR chi^2(14)	27.4933**	16.6007	29.2164***	16.8603	27.5159**	16.8256
Pseudo R2	0.0626	0.0367	0.0592	0.0368	0.0684	0.0311

Robust Standard errors in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

advanced irrigation technologies to achieve water-saving and efficiency-enhancement goals.

5.5 Implications for sustainable food systems

The findings of this study extend beyond irrigation technology adoption to illuminate broader dynamics of sustainable food systems transformation. The positive relationship between land consolidation, operational scale, and smart irrigation adoption reveals important pathways through which structural changes in agriculture can facilitate resource efficiency improvements. These pathways have implications for multiple dimensions of food system sustainability.

From an environmental perspective, the adoption patterns identified suggest potential for significant water savings and reduced environmental externalities in northern China's agricultural regions. Smart irrigation systems can reduce water consumption by 20%–40% compared to traditional methods while maintaining or improving yields (Zhang et al., 2020). At the regional scale documented in this study, widespread adoption could substantially alleviate pressure on groundwater resources and contribute to ecosystem sustainability. However, realizing these environmental benefits requires complementary policies that prevent rebound effects, where water savings enable expanded cultivation rather than conservation (Grafton et al., 2018).

Economically, the scale-dependent nature of adoption highlights tensions between efficiency gains and inclusivity in sustainable agricultural transitions. While large-scale operations can more readily invest in resource-efficient technologies, ensuring smallholder participation remains crucial for equitable food system transformation (Herrero et al., 2017). The heterogeneous effects observed across different contexts suggest that one-size-fits-all approaches to technology promotion are insufficient. Instead, differentiated support mechanisms that account for scale limitations, resource endowments, and institutional contexts are needed to enable inclusive sustainability transitions.

Socially, the study's findings underscore the importance of institutional factors, particularly government support, in facilitating technology adoption. This aligns with research emphasizing the role of enabling environments for sustainable food systems (Steiner et al., 2020). The stronger adoption effects in government-promoted areas suggest that public sector engagement can help overcome market failures and information asymmetries that impede sustainable technology diffusion. However, ensuring that such interventions reach diverse farmer groups and avoid exacerbating existing inequalities remains a critical policy challenge.

From a food security perspective, the adoption of smart irrigation in water-stressed northern China represents an adaptation strategy that can help maintain productivity under climate change (Wheeler and von Braun, 2013). The regional heterogeneity in adoption patterns, particularly the stronger effects in non-Yellow River irrigation areas and medium-low suitability

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TABLE 9 Heterogeneity analysis 2—regional corn suitability levels.

Variable	Adoption of smart irrigation technology					
	(1)	(2)	(3)	(4)	(5)	(6)
	High-suitability areas	Medium-low suitability areas	High-suitability areas	Medium-low suitability area	High-suitability areas	Medium-low suitability area
Average corn planting area per Plot	0.0311 (0.0516)	0.0652* (0.0360)				
Corn planting area			0.0059 (0.0236)	0.0209* (0.0107)		
Per capita corn planting area					−0.0332 (0.0654)	0.0857*** (0.0307)
Farmer individual characteristics	Controlled	Controlled	Controlled	Controlled	Controlled	Controlled
Household characteristics	Controlled	Controlled	Controlled	Controlled	Controlled	Controlled
Village characteristics	Controlled	Controlled	Controlled	Controlled	Controlled	Controlled
County-level fixed effects	Controlled	Controlled	Controlled	Controlled	Controlled	Controlled
Constant	1.2495	−5.0741**	1.1019	−4.9366**	1.3003	−6.1505***
	(1.5707)	(2.3144)	(1.5925)	(2.2846)	(1.5667)	(2.2872)
Number of observations	491	312	491	312	491	312
Log likelihood	−302.1082	−171.5998	−302.0202	−170.8207	−301.9517	−172.6639
LR $chi^2(14)$	17.0835	25.5180**	17.1643	28.5987***	17.5529	27.3498**
Pseudo R2	0.0297	0.0845	0.0300	0.0887	0.0302	0.0788

Robust Standard errors in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

TABLE 10 Heterogeneity analysis 3—location within the yellow river irrigation area.

Variable	Adoption of smart irrigation technology					
	(1)	(2)	(3)	(4)	(5)	(6)
	Yes	No	Yes	No	Yes	No
Average corn planting area per plot	0.0734 (0.1183)	0.0683** (0.0299)				
Corn planting area			−0.0049 (0.0371)	0.0222** (0.0092)		
Per capita corn planting area					−0.0608 (0.1295)	0.0773*** (0.0251)
Farmer individual characteristics	Controlled	Controlled	Controlled	Controlled	Controlled	Controlled
Household characteristics	Controlled	Controlled	Controlled	Controlled	Controlled	Controlled
Village characteristics	Controlled	Controlled	Controlled	Controlled	Controlled	Controlled
County-level fixed effects	Controlled	Controlled	Controlled	Controlled	Controlled	Controlled
Constant	4.7024	−1.1358	4.2203	−1.2479	5.4744	−1.8491
	(4.3029)	(1.3581)	(4.3220)	(1.3332)	(4.1761)	(1.4449)
Number of observations	106	696	106	696	106	696
Log likelihood	−60.3582	−411.6583	−60.2846	−411.6706	−60.2390	−414.1665
LR $chi^2(14)$	18.3973*	24.5752**	18.7961*	27.5239**	18.5550*	23.5326**
Pseudo R2	0.1467	0.0359	0.1477	0.0359	0.1484	0.0301

Robust standard errors in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

zones, indicates that resource-efficient technologies may be most valuable precisely where production conditions are most marginal. This suggests that targeted promotion of such technologies could contribute to food security by stabilizing production in vulnerable regions.

Finally, this study contributes to understanding circular economy principles in agricultural contexts. Smart irrigation systems enable more closed-loop management of water and nutrients, reducing waste and improving resource productivity. The finding that larger, more consolidated operations more readily adopt such technologies raises questions about optimal scales for circular agriculture and how to support circular practices across diverse farm types (Jurgilevich et al., 2016).

6 Conclusions

This study examined the role of land consolidation and large-scale operation in promoting smart irrigation technology adoption among maize farmers in northern China. Positioned within the broader context of sustainable food systems transformation, our findings provide insights into how structural changes in agriculture can facilitate resource-efficient technology diffusion and contribute to integrated sustainability objectives.

The analysis confirms that land consolidation and large-scale operation significantly promote smart irrigation adoption. Whether measured by total planting area, per capita planting area, or Average corn planting area per plot, operational scale demonstrates positive effects on technology uptake. These effects persist across multiple robustness checks and align with theoretical expectations regarding economies of scale and investment thresholds. Importantly, the magnitude of effects varies by institutional context, resource endowment, and regional suitability, highlighting the contingent nature of scale-technology relationships.

The heterogeneity analysis reveals critical insights for sustainable food systems policy. Government promotion amplifies scale effects, particularly for larger operators, suggesting that public support can catalyze technology diffusion but may require complementary measures to ensure inclusive access. The stronger effects observed in medium-low suitability areas and non-Yellow River irrigation zones indicate that resource-efficient technologies may offer greatest value where environmental constraints are most binding. This pattern suggests strategic opportunities for targeting technology promotion to enhance both productivity and sustainability in marginal agricultural areas.

6.1 Discussion

This study focuses on the role of land consolidation and large scale operation in promoting the adoption of smart irrigation technology among maize farmers in Northern China. Against the broader backdrop of the sustainable food system transition, our findings contribute to the existing literature and inform a wider discussion.

Consistency with and Extension of Existing Literature: Our results are consistent with a growing body of research that emphasizes the importance of structural and institutional factors in technology adoption. Specifically, we find that large scale operation, whether measured by total planting area, per capita planting area, Average corn planting area per plot, has a positive impact on the adoption of smart irrigation technology. This aligns with economic theories that propose economies of scale and investment thresholds. Our study extends the existing literature by providing empirical evidence from the context of a developing country with severe water constraints. The heterogeneity analysis shows that the effect of scale on smart irrigation adoption varies by institutional environment, resource endowment, and regional suitability. This indicates that while scale can facilitate technology adoption, the specific mechanisms and outcomes are context-dependent.

From a sustainable food systems perspective, these findings have several implications. First, they demonstrate that institutional arrangements governing land tenure and farm structure influence the feasibility of resource-efficient technology adoption. Policies supporting land consolidation and scale expansion may facilitate sustainability transitions, though attention to equity implications remains essential. Second, the study underscores the importance of differentiated approaches that account for regional heterogeneity in resources, institutions, and production conditions. Universal technology promotion strategies are unlikely to achieve optimal outcomes across diverse contexts.

Third, the findings illustrate how production-side innovations in resource efficiency connect to broader food system sustainability goals. Smart irrigation adoption contributes to environmental sustainability through water conservation, economic sustainability through improved productivity and input efficiency, and social sustainability through enhanced food security in water-stressed regions. However, realizing these multi-dimensional benefits requires integrated policy frameworks that address adoption barriers, prevent rebound effects, and ensure inclusive access to resource-efficient technologies.

Fourth, this study contributes empirical evidence for circular economy approaches in food production. Smart irrigation systems enable more precise and efficient resource use, reducing waste and environmental externalities. Understanding adoption determinants provides guidance for promoting circular practices in agriculture, though questions remain about optimal scales for circular systems and strategies for supporting diverse farm types in sustainability transitions.

Social Inclusion Considerations: Our discussion can extend to reflect on how to support smallholder farmers in accessing smart irrigation technology, ensuring that the sustainability transition is inclusive. While large-scale operations may more readily adopt capital-intensive technologies, ensuring that smallholders can access resource-efficient innovations is crucial for an equitable sustainability transition. This calls for policymakers to consider how to enable smallholders to adopt smart irrigation technology through financial incentives, technical training, and infrastructure support.

6.2 Policy recommendations for sustainable food systems

Based on these findings, we recommend several policy directions to advance sustainable food production in northern

China and similar contexts. First, governments should continue supporting land consolidation and tenure security reforms that enable farmers to make long-term investments in resource-efficient technologies. However, such reforms should incorporate safeguards to protect smallholder interests and ensure equitable access to consolidated land.

Second, technology promotion programs should adopt differentiated strategies that account for regional resource endowments, production conditions, and farmer characteristics. Priority should be given to water-scarce non-Yellow River irrigation areas and medium-low suitability zones where resource-efficient technologies offer greatest marginal value. Support mechanisms should address not only financial barriers but also information gaps, technical capacity constraints, and infrastructure limitations.

Third, policies should promote integrated approaches that combine technology adoption with complementary practices such as improved crop varieties, optimized fertilization, and soil conservation. Such integration can enhance overall resource use efficiency and contribute to circular economy principles in food production. Extension services and farmer training programs should emphasize systems thinking and resource stewardship alongside specific technology adoption.

Fourth, monitoring and evaluation frameworks should assess not only adoption rates but also realized environmental and social outcomes. This includes tracking water savings, yield impacts, economic returns, and distributional effects across farmer groups. Such comprehensive assessment can inform adaptive policy design and ensure that technology promotion contributes to equitable and sustainable food system transformation.

6.3 Limitations and future research

This study has several limitations that suggest directions for future research. First, the cross-sectional design limits causal inference and precludes analysis of adoption dynamics over time. Longitudinal studies tracking technology adoption and outcomes across multiple seasons would provide stronger evidence regarding causal relationships and long-term sustainability impacts. Second, the geographic scope is limited to northern China's maize systems. Comparative research across crops, regions, and countries could illuminate how context shapes scale-technology relationships and inform transferability of findings. Third, the study focuses primarily on adoption decisions rather than realized outcomes. Future research should examine actual water savings, yield effects, profitability, and environmental impacts of smart irrigation adoption across different scales and contexts. Fourth, while the study considers socioeconomic factors, deeper qualitative investigation of farmer decision-making, social networks, and institutional influences could enrich understanding of adoption processes. Mixed-methods approaches combining quantitative analysis with ethnographic research would be valuable.

Fifth, the study does not address potential trade-offs or unintended consequences of technology promotion, such as rebound effects, labor displacement, or inequitable distribution of benefits. Critical assessment of sustainability interventions requires attention to such complexities. Finally, future research should examine pathways for inclusive technology access that enable smallholder participation in sustainability transitions without requiring consolidation or scale expansion that may be socially or economically disruptive.

Despite these limitations, this study provides important evidence regarding drivers of resource-efficient technology adoption in water-stressed agricultural regions. The findings contribute to understanding sustainable food systems transformation by illuminating how structural factors, institutional support, and resource contexts shape farmers' capacity to adopt practices that advance environmental, economic, and social sustainability objectives. As global food systems confront mounting pressures from climate change, resource scarcity, and population growth, such insights become increasingly valuable for designing policies and interventions that can support sustainable intensification, circular economy principles, and equitable food security.

Data availability statement

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

Author contributions

SZ: Conceptualization, Writing – review & editing, Resources, Visualization, Validation, Writing – original draft. HX: Supervision, Writing – review & editing, Methodology, Visualization, Software.

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