



OPEN ACCESS

EDITED BY

Umer Farrukh,
Government College Women University
Sialkot, Pakistan

REVIEWED BY

Hui Mao,
Shaanxi Normal University, China
Yu Liu,
Nanjing University of Finance and Economics,
China

*CORRESPONDENCE

Xueming Zai
✉ zxm1@jit.edu.cn
Yulan Song
✉ syl421@163.com

RECEIVED 25 June 2025

ACCEPTED 20 August 2025

PUBLISHED 09 September 2025

CITATION

Yuan Y, Zhu X, Wang C, Zai X, Song Y and
Amar N (2025) Impact of farm size on
pesticide use: evidence from Chinese rice
production.
Front. Sustain. Food Syst. 9:1653777.
doi: 10.3389/fsufs.2025.1653777

COPYRIGHT

© 2025 Yuan, Zhu, Wang, Zai, Song and Amar.
This is an open-access article distributed
under the terms of the [Creative Commons
Attribution License \(CC BY\)](#). The use,
distribution or reproduction in other forums is
permitted, provided the original author(s) and
the copyright owner(s) are credited and that
the original publication in this journal is cited,
in accordance with accepted academic
practice. No use, distribution or reproduction
is permitted which does not comply with
these terms.

Impact of farm size on pesticide use: evidence from Chinese rice production

Yinghui Yuan¹, Xiaowei Zhu¹, Changyi Wang¹, Xueming Zai^{1*},
Yulan Song^{2*} and Nimra Amar³

¹School of Horticulture and Landscape Architecture, Jinling Institute of Technology, Nanjing, China,

²College of Economics and Management, Xinjiang Agricultural University, Urumchi, China, ³College of Economics and Management, Huazhong Agricultural University, Wuhan, China

Introduction: China's position as the world's largest consumer of chemical pesticides presents a critical challenge to the long-term sustainability of its food production systems. While vital for past food security achievements, the excessive application of these chemicals now degrades agro-ecological health and hinders sustainable agricultural development. Many studies have investigated technological fixes, yet a key structural question remains: how does farm size affect chemical dependency?

Methods: This study employs a 2SLS model and uses farm-level rice data from Jiangsu Province (2004–2017) to analyze the impact of farm size on pesticide costs.

Results and discussion: We find a U-shaped relationship between farm size and pesticide use. At the sample mean, a 1% increase in farm size is associated with a 0.089% decrease in pesticide cost per unit of land (mu) and a 0.104% decrease per kilogram of rice. This finding suggests that for the majority of farms, increasing scale is currently aligned with greater pesticide use efficiency. It challenges the notion that small-scale farming is inherently more sustainable, indicating that an optimal scale exists for minimizing chemical dependency. The paper concludes with policy implications for designing pathways toward a more sustainable, low-input food system in China.

KEYWORDS

farm size, pesticide use, sustainable agriculture, U-shaped relationship, China

1 Introduction

Achieving global food security in the 21st century requires navigating a fundamental dilemma: how to produce enough food for a growing population while ensuring the long-term sustainability of our food production systems. Chemical pesticides have been a double-edged sword in this pursuit. On one hand, they have been instrumental in securing crop yields and advancing modern agriculture over the past four decades, particularly in China (Popp et al., 2013; Zhang et al., 2011; Beddington, 2010; Rahman, 2013; Yuan and Zhang, 2021; Zhang and Yu, 2021). Globally, pests and plant diseases can reduce food production by up to 35% annually (Wang et al., 2017), and chemical interventions have been the primary tool to mitigate these losses. In China, for instance, without pesticides, the production of key crops could fall by as much as 32–78% (Cai, 2008; Bu et al., 2014), underscoring their historical importance.

However, this reliance on chemical inputs has come at a significant cost to agro-ecological health and long-term sustainability. The overuse of herbicides, insecticides, and fungicides is now a defining challenge for Chinese agriculture (Jin et al., 2017). With an estimated use efficiency of only 35%, a substantial volume of these chemicals enters the environment, contaminating soil, water, and air (Ministry of Agriculture and Rural Affairs of the People's Republic of China (MOARA), 2015). Despite regulations, highly toxic and persistent pesticides

remain in use (Zhang and Lu, 2007), while their residues accumulate in the food chain, posing severe risks to human health (Kavlock et al., 1996). This trajectory is incompatible with the goals of sustainable development and threatens the resilience of the very agricultural systems upon which food security depends.

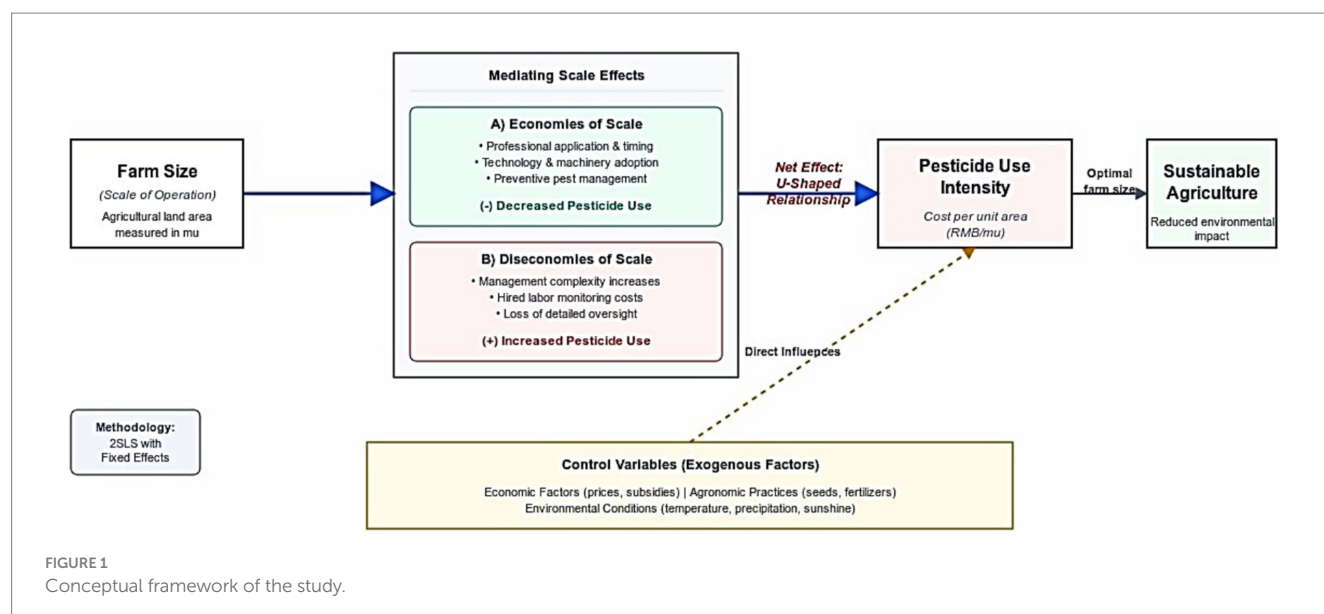
In response, China has pursued policies to curb chemical use, such as the “zero growth” action plan for pesticides by 2020, which promotes alternative technologies and management practices (Ministry of Agriculture and Rural Affairs of the People’s Republic of China (MOARA), 2015). Research has validated the potential of methods like soil testing and biological controls (Zhang et al., 2015; Ju et al., 2016; Zhang et al., 2017). However, the adoption of these knowledge-intensive solutions is hindered by the prevailing farm structure. Chinese agriculture is dominated by smallholders who often have lower levels of education and scientific knowledge (Cui et al., 2018; Zhang et al., 2023a). With agriculture becoming a secondary source of income for many rural households, there is little incentive for small-scale farmers to invest in new, sustainable practices (Ju et al., 2016). This structural reality presents a major barrier to a nationwide sustainable transition.

Amidst these challenges, institutional changes and rural labor migration have encouraged farm size expansion, leading to a significant increase in moderate and large-scale farming operations (Zhang et al., 2019; Huang and Ding, 2016; Hu et al., 2019; Zhang et al., 2023b). Zhang et al. (2019) point out that although the average farm size decrease from 10 mu in 1997 to 7 mu in 2014 in China, the number of larger farms with farm size greater than 50 mu increased from 1.21 million in 1997 to 1.56 million in 2013, and their operation scale account for 20.7% of the total arable land in China. This structural shift offers a potential pathway toward more sustainable production. Theoretically, larger farms may be more professional, have better access to technology and machinery, and possess greater agricultural knowledge, leading to more efficient and reduced pesticide application (Adamopoulos and Restuccia, 2014). Conversely, some evidence suggests small farms can be more productive due to detailed management and lower supervision costs, potentially leading to less chemical wastage (Lau and Yotopoulos,

1971; Akamin et al., 2017; Larson et al., 2012; Henderson, 2015; Ali and Deininger, 2015).

This conflicting evidence presents a critical research gap. While some studies in China suggest a simple negative correlation between farm size and chemical inputs (Wu et al., 2018; Ren et al., 2019; Hu et al., 2019; Gao et al., 2021), others find no such effect, particularly for fertilizers (Xu, 2020). The relationship remains ambiguous, leaving a crucial question for policymakers: What is the true impact of farm size on pesticide use? Due to a large number literature found U-shaped relationship between farm size and productivity or production costs (Sheng et al., 2019; Zhang et al., 2019), this paper moves beyond the assumption of a simple linear effect to investigate a more complex, non-linear relationship. We hypothesize that the connection between farm size and pesticide use is not monotonic, but rather follows a U-shaped curve, where pesticide costs initially decrease with scale before eventually increasing.

This paper contributes to the literature on sustainable food production in three important ways. First, by examining the non-linear nature of the farm size-pesticide link, we provide crucial evidence for designing effective policies that promote moderate-scale operations as a pathway to sustainability. Although both fertilizer and pesticide are taken as chemical inputs, pesticide is a damage-abating input for improving growth conditions, while fertilizer is a growth input directly involving in biological process of rice growth. Pesticides may be more sensitive to farm size. Second, we utilize a robust, long-term micro-level dataset (2004–2017) from Jiangsu Province, focusing on rice—a crop central to both food security and pesticide consumption in China. Third, we employ a rigorous 2SLS model with farm-fixed effects to address endogeneity and measurement errors, allowing for a more precise estimation of the causal impact of farm size. Our central finding confirms the U-shaped relationship, suggesting that while expanding from a small base can reduce pesticide intensity, there is an optimal scale beyond which diseconomies may lead to increased chemical dependency. Based on the literature and the context of Chinese agriculture, we propose the conceptual framework in Figure 1 to illustrate the hypothesized non-linear relationship between farm size and pesticide use, which this study will empirically test.



The structure of this paper is as follows: Section 2 introduces relevant background information. Methodology and data are presented in Section 3, Section 4 shows the empirical results and discussion, and Section 5 concludes.

2 Context: pesticide trends and agricultural restructuring in China

China's role in global food production is intrinsically linked to its status as the world's largest consumer of chemical pesticides. Since 2006, pesticide usage has been a cornerstone of its agricultural strategy, yet this has created significant sustainability challenges. Usage rates surged dramatically in recent decades (Jin et al., 2017), with total application peaking at 0.35 million tons in 2013 and intensity reaching 2.64 kg/ha in 2014 (Food and Agriculture Organization of the United Nations, 2018; Figure 1). Recognizing this unsustainable trajectory, the Ministry of Agriculture (MOA) intervened in 2015 with a national action plan to achieve zero growth in pesticide use. The plan promoted a multi-pronged strategy, including the adoption of non-chemical controls, the substitution of high-risk pesticides with safer alternatives, and the promotion of scientific application techniques to improve efficiency and reduce waste. This policy response underscores the urgency of the issue, especially as China is also a leading global producer and exporter of pesticides (Zhang et al., 2011), and its domestic demand is projected to remain high (Li et al., 2014).

An examination of recent trends suggests a potential shift. As illustrated in Figure 2, national pesticide use has declined from its 2014 peak. While this trend coincides with the implementation of the MOA's policy interventions, attributing the change solely to these top-down measures would be an oversimplification. Critically, this same period witnessed a profound structural transformation in Chinese agriculture. Spurred by innovations in farmland institutions, new types of agricultural operators, such as large-scale households, family farms, and cooperatives, have become

increasingly prevalent, leading to a significant rise in the average farm size, particularly since the 2010s.

This parallel development creates an analytical challenge: is the observed reduction in pesticide use a result of direct policy measures, or is it also influenced by the underlying consolidation of farmland? It is crucial to disentangle the effects of these concurrent trends. Therefore, to design effective policies for a sustainable future, it is imperative to first understand the specific relationship between farm size and farmers' chemical use behavior. This study addresses this question directly by investigating the impact of farm scale on pesticide application.

3 Methodology and data

3.1 Empirical strategy and model specification

To investigate the non-linear impact of farm size on pesticide use, we employ a panel data approach that accounts for the potential endogeneity of farm size. Given the diversity in pesticide formulations (e.g., powders, liquids), standardizing application by quantity is problematic. Consequently, we use the annual cost of pesticides per unit of area (mu) as our primary dependent variable, a common proxy in the literature. To ensure our findings are robust, we also use the pesticide cost per kilogram of rice as an alternative dependent variable. Our study focuses specifically on rice farmers in Jiangsu Province from 2004 to 2017, distinguishing our work from broader studies on grain farmers (e.g., Wu et al., 2018).

While some research suggests a simple negative correlation between farm size and agrochemical use (Wu et al., 2018; Ren et al., 2019), other studies indicate that the smallest farms can achieve high input-use efficiency (Hu et al., 2019), hinting at a more complex relationship. To test this, we introduce a quadratic term for farm size into our model to capture a potential non-linear, U-shaped effect.

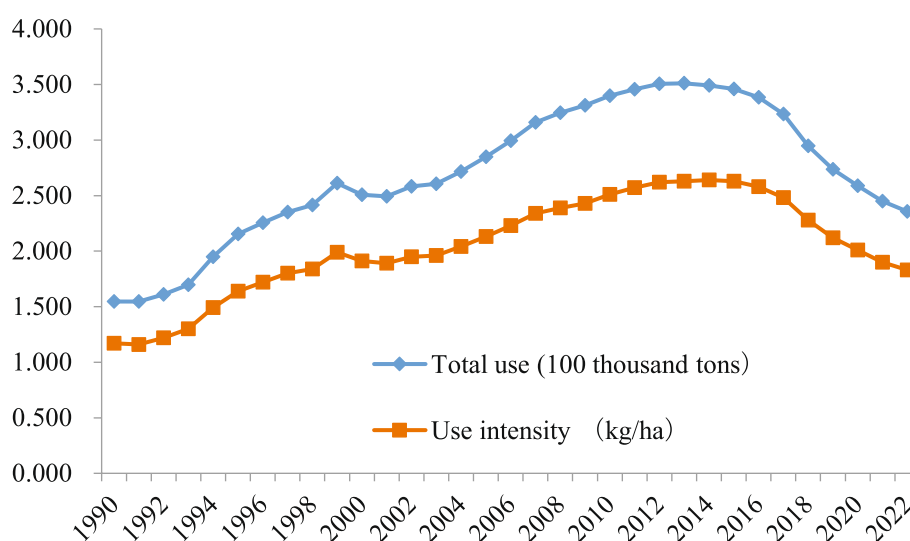


FIGURE 2
The total use and use intensity of chemical pesticide in China from 1990 to 2022.

Our baseline specification is a fixed-effects model as shown in Equation 1:

$$\ln Y_{it} = \alpha_0 + \alpha_1 \ln size_{it} + \alpha_2 \ln size_{it}^2 + \alpha_3 Z_{it} + v_i + v_t + \varepsilon_{it} \quad (1)$$

Where:

- Y_{it} is the pesticide cost for farmer i in year t .
- $size_{it}$ is the key independent variable.
- Z_{it} is a vector of control variables selected for their influence on pesticide use. These include: (1) Economic factors such as the price of fertilizer (as a proxy for pesticide prices), seed price, previous year's rice price, agricultural subsidies, and county-level per capita GDP. According to supply and demand theory, the price of pesticides affects their usage. In addition, agricultural subsidies can alleviate liquidity constraints for farmers, but their specific use is still determined by pests and diseases. (2) Agronomic factors such as the quantity of seeds used per mu (as higher planting density can increase pest pressure) and the previous year's yield (as a proxy for land quality and farmer skill). (3) Climatic conditions such as the annual temperature, precipitation, and sunshine duration, which significantly impact pest proliferation and pesticide efficacy (Maor, 2019; Delcours et al., 2015; Chen and McCarl, 2001; Sparks, 2001).
- v_i represents individual fixed effects to control for time-invariant unobserved factors like innate farmer ability and soil quality.
- v_t represents time fixed effects to control for year-specific shocks.
- ε_{it} is the error term.

3.2 Endogeneity and the 2SLS approach

The fixed-effects model may still produce biased estimates if farm size is endogenous—that is, correlated with unobserved time-varying factors. For example, farmers who expand their operations may acquire land of different quality, which could influence pesticide needs. To address this endogeneity problem, we employ a two-stage least squares (2SLS) instrumental variable (IV) approach (Sheng et al., 2019).

Following the precedent of Sheng et al. (2019) and Zhang et al. (2023a, 2023b), we use the lagged farmers' rice commodity rate as our instrument. This rate, defined as the proportion of production sold versus consumed by the household, is a strong candidate for a valid IV. It is highly correlated with the decision to expand farm size (relevance), as a higher commodity rate signifies greater market orientation and productivity, making expansion more likely. However, as a lagged variable determined by past conditions, it is unlikely to be correlated with unobserved factors, such as the quality of leased farmland that affects current-year pesticide use (exclusion restriction).

The 2SLS estimation proceeds in two stages, and the first stage and second stage are shown in Equations 2, 3, respectively:

- (1) First Stage: we regress the endogenous variable (farm size) on the instrumental variable and all other exogenous controls to generate a predicted value for farm size.

$$\ln size_{it} = \beta_0 + \beta_1 R_{it} + \beta_2 Z_{it} + v_i + v_t + \mu_{it} \quad (2)$$

- (2) Second Stage: we replace the observed farm size in Equation 1 with its predicted value $\ln \hat{size}_{it}$ from the first stage.

$$\ln Y_{it} = \alpha_0 + \alpha_1 \ln \hat{size}_{it} + \alpha_2 \ln \hat{size}_{it}^2 + \alpha_3 Z_{it} + v_i + v_t + \varepsilon_{it} \quad (3)$$

This 2SLS procedure allows for a more robust and unbiased estimation of the causal impact of farm size on pesticide costs.

3.3 Data and descriptive statistics

This study utilizes a rich panel dataset from the agricultural production cost–benefit database, a comprehensive survey routinely managed by China's National Development and Reform Commission (NDRC). The farm-level data for this research was collected by the Price Bureau of Jiangsu Province, covering 300 to 340 households annually across 37 counties between 2004 and 2017. To ensure the sample is representative, a three-stage stratified sampling procedure was used to select counties, townships, and individual farms. In sampling townships, we divide farmers into three groups based on farm size: large, medium and small group. We then select an appropriate number of samples based on the proportion of farmers in each group. To maintain the comparability of survey data, once survey households are determined, they are not adjusted for 5 years in principle. If a survey household disappears or loses its representativeness, a replacement household will be selected from the original group to which the household belonged. Furthermore, the data used in this paper is subject to minimal measurement error. First, the data was recorded by farmers in the form of accounting records, and farmers receive training every year. Second, experienced staffs were hired to carefully check each piece of data and identify any possible anomalies. The data's quality has been confirmed by Fan and Connie (2005).

Jiangsu Province serves as a particularly relevant case study for this analysis. As an economically advanced region and a significant grain producer, its agricultural practices often signal national trends. More importantly, it is an ideal setting to study the nexus of farm size and pesticide use. Rice is the primary crop driving pesticide consumption in China, accounting for 15% of total sales (Zhang et al., 2011). Jiangsu is the nation's fifth-largest rice-producing province, contributing 9.23% of the total yield (Zhang et al., 2023b), and the intensity of its pesticide use is crucial for achieving high output. Therefore, findings from Jiangsu's rice sector have significant implications for China's broader sustainable agriculture policies.

Table 1 provides descriptive statistics for the 4,661 farm-year observations in our sample. The data reveals two critical trends. First, the average cost of pesticides was 67.56 RMB per mu and 12.08 RMB per 100 kilograms of rice. Second, the study period was characterized by a dramatic structural shift in farm scale. The average farm size in the sample expanded from just 3.96 mu in 2004 to 99.44 mu in 2017, with a mean of 16.55 mu over the entire period. This confirms that our data captures the significant trend of farm consolidation occurring in the province. The characteristics of the sample farmers reflect the general attributes of those in Jiangsu, ensuring a strong degree of representativeness for our analysis.

4 Results and discussions

4.1 Preliminary analysis: fixed-effects model results

The challenge of achieving sustainable agricultural production requires balancing crop output with reduced chemical dependency. While our descriptive analysis indicates a concurrent rise in farm size and pesticide use, a simple correlation is insufficient for understanding the true relationship. Pesticide application is influenced by a host of confounding factors, including input prices, agronomic practices, and climatic conditions. Therefore, to isolate the specific impact of farm size, we first employ a fixed-effects panel data model. This approach allows us to control for time-invariant

unobserved variables such as innate farmer skill and land quality, providing a more precise preliminary estimate.

Table 2 presents the results of this fixed-effects estimation. It is worth noting that while the model's R-squared value is modest, this is common in panel data analyses using high-dimensional fixed effects. Our primary objective is not to maximize predictive power but to obtain unbiased coefficients for the variables of interest, particularly farm size. Column (1) shows that when only a linear term for farm size is included, the effect on pesticide cost per mu is statistically insignificant. This initial result suggests that a simple, linear relationship is inadequate to capture the complexities of farmer behavior.

To test our central hypothesis of a non-linear effect, we introduce a quadratic term for farm size in column (2).

TABLE 1 Descriptive statistics of key variables.

Variables definition	Mean	Std. Dev.	Min	Max
Cost of chemical pesticide per mu (RMB)	67.56	23.85	0	211.36
Cost of chemical pesticide per 100 kilogram Rice (RMB)	12.08	4.62	0	43.52
Farm size (mu)	16.55	92.53	0.40	2650
Prices of chemical fertilizers per kilogram (RMB)	3.46	0.57	1.99	6.64
Quantity of seeds per mu (Kilogram)	5.05	2.16	0.75	16.30
Price of seeds per kilogram(RMB)	5.16	5.65	0.50	88.13
Price of rice per kilogram (RMB)	1.67	0.16	1.24	2.58
Temperature (°C)	22.18	0.96	20.10	24.22
Precipitation (mm)	394.70	7602.94	21.60	166715.80
Sunshine duration (Hour)	162.10	24.38	109.43	229.18
Yield in the previous year (Kilogram)	563.43	59.11	300	743
Per capital GDP on county level (RMB)	36252.79	25322.56	4096.35	160663.2

1 hectare = 15 mu, 1 USD = 7.19 RMB. Statistics are based on 4,661 farm-year observations from rice farmers in Jiangsu Province, 2004–2017.

TABLE 2 Fixed-effects OLS estimates of the impact of farm size on pesticide cost per mu.

Variables	Chemical pesticide application per mu		
	(1)	(2)	(3)
Farm size in log form	0.017 (0.01)	−0.043* (0.02)	−0.110*** (0.02)
The square of Farm size in log form		0.015*** (0.01)	0.023*** (0.01)
Prices of chemical fertilizers			0.079*** (0.01)
Quantity of seeds in log form			0.012*** (0.00)
Prices of seeds			0.002** (0.00)
Price of rice in last year			−0.149*** (0.04)
Yield in last year			−0.019 (0.05)
Subsidy			−0.014 (0.02)
Temperature in log form			−0.912*** (0.21)
Precipitation in log form			0.008 (0.01)
Sunshine duration in log form			0.082** (0.03)
Per capital GDP in log form			0.225*** (0.03)
Constants	4.455*** (0.02)	4.490*** (0.02)	4.600*** (0.72)
Number of observations	4316	4316	3459
R-squares	0.001	0.003	0.112

Standard errors in parentheses; *, ** and *** are significance at 10, 5, and 1%, respectively.

The results are striking: the linear term becomes negative and statistically significant, while the quadratic term is positive and highly significant. This provides strong preliminary evidence of a U-shaped relationship, where pesticide costs initially decrease as farms expand from a small base, but then begin to increase after reaching a certain scale. This core finding holds and gains statistical significance when we introduce the full set of control variables in column (3). The persistence of the U-shaped relationship after accounting for economic, agronomic, and climatic factors underscores its robustness.

The economic intuition behind this U-shaped curve reflects a transition from economies to diseconomies of scale in pest management. The initial downward slope can be attributed to professionalization. As small-scale farmers expand, they may gain better access to agricultural technical services and adopt more efficient application technologies, reducing waste (Yin and Yu, 2019). This represents a phase of increasing efficiency. However, the upward slope suggests that beyond an optimal point, managerial challenges emerge. As farm size continues to increase, farmers may be constrained by land availability and find it more economical to intensify chemical use rather than invest in more land or machinery (Ju et al., 2016). Furthermore, supervising hired labor becomes more difficult, timely pest monitoring across vast plots is compromised, and spary pesticide in time is impossible, potentially leading to a higher overall application intensity.

4.2 Main causal effects: 2SLS endogeneity-corrected results

While the fixed-effects model provided initial evidence of a U-shaped curve, its estimates may be biased due to the potential endogeneity of farm size. To obtain a more reliable causal estimate, we therefore turn to the 2SLS model. Table 3 presents the results of this approach, including the necessary diagnostic tests that validate its use.

Before interpreting the main findings, it is crucial to confirm the validity of our instrumental variable. The results from the first-stage regression (Columns 1 and 2) show that our instrument, the lagged commodity rate, is a significant predictor of farm size. More formally, the underidentification test (Kleibergen-Paap LM statistic) is highly significant ($p = 0.00$), confirming that our model is correctly identified and the instrument is relevant. Furthermore, the Hausman test for endogeneity yields a p -value of 0.01, allowing us to reject the null hypothesis that farm size is an exogenous variable. Together, these tests confirm that endogeneity is a significant issue and that the 2SLS approach is both necessary and appropriate. We therefore focus our analysis on these more robust 2SLS results.

Based on the estimations in Column (3) of Table 3, we find that the U-shaped relationship between farm size and chemical pesticide use remain constant. More specifically, 1% increase in farm size will lead to a 0.089% decrease in the cost of chemical pesticide used per mu according to the margin effect of chemical pesticide use on farm size. The 2SLS uses a point estimation approach, implying that increasing the size can still reduce pesticide costs at the current

TABLE 3 2SLS instrumental variable (IV) estimates of the impact of farm size on pesticide cost per mu.

Variables	First stage of 2SLS		Second stage of 2SLS
	Farm size in log form	The square of Farm size in log form	Chemical pesticide application per mu
	(1)	(2)	(3)
Instrument variable: Commodity rate	−0.001** (0.00)	−0.052*** (0.01)	
Instrument variable: The square of commodity rate	0.001*** (0.00)	0.001*** (0.00)	
Farm size in log form			−0.296*** (0.09)
The square of Farm size in log form			0.053** (0.03)
Prices of chemical fertilizers	−0.001 (0.02)	−0.228** (0.00)	0.051*** (0.02)
Quantity of seeds in log form	0.018*** (0.01)	0.056** (0.02)	0.014*** (0.00)
Prices of seeds	−0.008*** (0.00)	−0.032*** (0.01)	0.002 (0.00)
Price of rice in last year	0.467*** (0.18)	3.008*** (0.079)	0.105 (0.12)
Yield in last year	−0.188** (0.08)	−0.984*** (0.36)	−0.118** (0.05)
Subsidy	0.096* (0.05)	0.157 (0.221)	−0.085*** (0.03)
Temperature in log form	1.445** (0.72)	3.269 (3.24)	−1.811*** (0.46)
Precipitation in log form	−0.011 (0.01)	0.016 (0.06)	0.016* (0.01)
Sunshine duration in log form	−0.111 (0.10)	−0.697 (0.46)	−0.172*** (0.07)
Per capital GDP in log form	−0.012 (0.05)	−1.194*** (0.01)	0.272*** (0.05)
Hausman Test for Endogeneity (p value)			0.01
Under identification test			0.00
Number of observations	4316	4316	3459
R-squares			0.112

Standard errors in parentheses, *, ** and *** are significance at 10, 5, and 1%, respectively.

average size of 16.55 mu¹. In other words, the result indicates that the current farm size is on the left side of the U-shaped curve, and chemical pesticide use will decrease as farm size increase. Thus, there is some potential for reducing pesticide use by expanding farm size. However, it is not the case that the larger the farm size, the lower the cost of pesticides per unit area. With the expansion of the farm size, although the bargaining power of farmers to buy pesticide increased, but also face a series of problems, resulting in a rise in the cost of pesticides per unit area. First, farmers are too busy to rely on their own labor, the need to hire labor, the hired labor will lead to higher supervision costs, affecting the effectiveness of pesticide use. Second, farmers are unable to monitor the pest and disease situation of each plot of land in a timely manner, which may lead to untimely spraying. This affects the quality of pesticide use and increasing the cost of pesticides per unit area. However, As farm size expands and farmers become more specialized, it is possible to greatly reduce pesticide use by predicting the occurrence of pests and diseases in advance and suppressing them in the early stages of an outbreak. We will study this phenomenon in the future work.

4.3 The effects of other production and climatic factors

Beyond the primary impact of farm size, our 2SLS model (Table 3) also reveals the significant influence of several economic, agronomic, and climatic factors on farmers' pesticide costs. This section discusses these secondary, yet important, findings.

Among the economic variables, the price of chemical fertilizers has a statistically significant positive effect on pesticide costs, with a coefficient of 0.051 ($p < 0.01$). In local agricultural markets, fertilizer and pesticide prices often move in tandem. Thus, a rising fertilizer price acts as a proxy for a rising pesticide price. While a higher price may lead to a reduction in the quantity of pesticides purchased, the demand for pest control is relatively inelastic, meaning the overall expenditure (cost) still increases. In contrast, the previous year's rice price and agricultural subsidies were found to have no significant effect. The insignificance of subsidies, though they can ease liquidity constraints (Yi et al., 2015; Ge and Zhou, 2012), is logical. Pesticide application is primarily a reactive measure to pest and disease outbreaks, rather than a planned input directly influenced by subsidy payments.

Agronomic decisions also play a crucial role. Seed quantity is positively and significantly associated with pesticide costs, with a coefficient of 0.014. This implies that a 1% increase in seed usage per mu is linked to a 0.014% increase in pesticide expenditure. The explanation is straightforward: higher seed quantity leads to greater planting density, which can increase canopy humidity and the likelihood of crop diseases, thereby necessitating greater pesticide use. Conversely, the previous year's yield, used here as a proxy for land quality and farmer capacity, has a significant negative effect. This

suggests that farms with better soil quality or more skilled operators tend to have healthier, more resilient crops that require less chemical intervention.

Climatic conditions are, unsurprisingly, strong determinants of pesticide application. We find a significant negative relationship between temperature and pesticide costs; a 1% increase in average temperature is associated with a 1.811% decrease in costs. A plausible explanation is that high temperatures can increase the volatility and phytotoxicity of certain chemicals, leading farmers to apply less to avoid crop damage or human health risks. In contrast, precipitation has a significant positive impact, with a 1% increase in rainfall associated with a 1.6% increase in pesticide costs. Although rice is a water-intensive crop, excessive rainfall can foster fungal pathogens and exacerbate pest problems, thereby increasing the need for chemical treatments (Chen and McCarl, 2001). Finally, sunshine duration has a significant negative effect, as increased sun exposure promotes vigorous plant growth and metabolism, enhancing the crop's natural ability to withstand pests and diseases.

4.4 Robustness check

To ensure the validity of our findings, we conduct a key robustness check that accounts for farm productivity. Our primary analysis uses pesticide cost per unit of area, which does not consider variations in yield. A farm could have higher costs per area but be more efficient per unit of output (Valenciano et al., 2005). Therefore, we re-estimate our models using an alternative dependent variable: pesticide cost per kilogram of rice.

The results of this check, presented for both the fixed-effects (Table 4) and 2SLS models (Table 5), are highly consistent with our primary findings. Most importantly, the U-shaped relationship between farm size and pesticide intensity persists. The endogeneity-corrected 2SLS model shows that at the sample mean, a 1% increase in farm size results in a 0.104% decrease in the pesticide cost per kilogram of rice. This confirms that our central conclusion is not an artifact of the chosen metric. It strengthens the evidence that, on average, the farms in our sample are operating on the downward-sloping portion of the U-curve, where moderate scale expansion aligns with greater input efficiency.

5 Conclusion

This study sought to address a central tension in China's pursuit of sustainable agriculture: the complex and often misunderstood relationship between farm scale and chemical dependency. Using a robust 2SLS model on a 14-year panel dataset of rice farms in Jiangsu Province, we move beyond the assumption of a simple linear relationship. Our analysis reveals a distinct U-shaped impact of farm size on pesticide costs, measured both per unit of area and per unit of output. This finding suggests that an optimal, moderate scale exists where pesticide use efficiency is maximized.

From a public policy perspective, our findings are significant for designing pathways toward a low-input, sustainable food system.

First, the results validate promoting moderate farm size expansion as a viable strategy to reduce overall pesticide intensity. For the majority of farms still operating on the left side of the U-curve,

1 The turning point is 16.5 mu by using the U-shaped parabolic method. However, simply using the U-shaped parabolic method to calculate the turning point is problematic because it is not a simple one-quadratic parabola and there are many other controlling factors.

TABLE 4 Robustness check: fixed-effects OLS estimates with pesticide cost per 100 kg rice as the dependent variable.

Variables	Chemical pesticide application per kilogram rice		
	(1)	(2)	(3)
Farm size in log form	0.018 (0.01)	−0.061*** (0.02)	−0.104*** (0.02)
The square of Farm size in log form		0.020*** (0.01)	0.026*** (0.01)
Prices of chemical fertilizers			0.073*** (0.01)
Quantity of seeds in log form			0.010*** (0.00)
Prices of seeds			0.002 (0.00)
Price of rice in last year			−0.242*** (0.04)
Yield in last year			0.022 (0.05)
Subsidy			−0.092*** (0.02)
Temperature in log form			−0.932*** (0.21)
Precipitation in log form			0.009 (0.01)
Sunshine duration in log form			0.057* (0.03)
Per capital GDP in log form			0.180*** (0.03)
Constants	−1.882*** (0.02)	−1.835*** (0.02)	−0.969 (0.77)
Number of observations	4661	4661	3458
R-squares	0.001	0.004	0.046

Standard errors in parentheses; *, ** and *** are significance at 10, 5, and 1%, respectively.

TABLE 5 Robustness check: 2SLS IV estimates with pesticide cost per 100 kg rice as the dependent variable.

Variables	First stage of 2SLS		Second stage of 2SLS
	Farm size in log form	The square of Farm size in log form	Chemical pesticide cost per 100 kilogram rice
	(1)	(2)	(3)
Instrument variable: Commodity rate	−0.001** (0.00)	−0.052*** (0.01)	
Instrument variable: The square of commodity rate	0.001*** (0.00)	0.001*** (0.00)	
Farm size in log form			−0.319*** (0.10)
The square of Farm size in log form			0.055** (0.03)
Prices of chemical fertilizers	−0.001 (0.02)	−0.228** (0.00)	0.047*** (0.02)
Quantity of seeds in log form	0.018*** (0.01)	0.056** (0.02)	0.014*** (0.00)
Prices of seeds	−0.008*** (0.00)	−0.032*** (0.01)	0.001 (0.00)
Price of rice in last year	0.467*** (0.18)	3.008*** (0.079)	0.155 (0.13)
Yield in last year	−0.188** (0.08)	−0.984*** (0.36)	−0.097* (0.06)
Subsidy	0.096* (0.05)	0.157 (0.221)	−0.087*** (0.03)
Temperature in log form	1.445** (0.72)	3.269 (3.24)	−1.541*** (0.49)
Precipitation in log form	−0.011 (0.01)	0.016 (0.06)	0.023*** (0.01)
Sunshine duration in log form	−0.111 (0.10)	−0.697 (0.46)	−0.148*** (0.07)
Per capital GDP in log form	−0.012 (0.05)	−1.194*** (0.01)	0.298*** (0.05)
Hausman Test for Endogeneity (<i>p</i> value)			0.00
Under identification test			0.00
Number of observations	4316	4316	3459
R-squares			0.057

Standard errors in parentheses; *, ** and *** are significance at 10, 5, and 1%, respectively.

consolidation can lead to greater efficiency, helping to advance national goals like the “zero growth” pesticide action plan. However, expanding farm size through land leasing faces high transaction costs. Fortunately, China implemented Three Rights Separation

reform in 2013 to promote market-oriented land leasing (Zhang et al., 2023a, 2023b). Therefore, it is necessary to make full use of this land institution innovation to promote moderate-scale land operations.

Second, our findings call for targeted, scale-appropriate policies. A one-size-fits-all approach is insufficient. For smallholder farmers unable to expand, policy should focus on creating access to shared resources and socialized services. Cooperative purchasing and professional spraying services can allow smallholders to benefit from economies of scale in pest management without altering their land size. For large-scale farms operating near or beyond the curve's turning point, support should focus on overcoming managerial diseconomies. This includes promoting advanced application technologies like drones and precision sprayers to improve efficiency and reduce labor supervision costs, as well as investing in digital pest-monitoring systems.

Finally, we acknowledge the limitations of this study, which in turn open avenues for future research. First, our use of pesticide *cost* data, while necessary, cannot perfectly distinguish between changes in the *quantity* of pesticides used and fluctuations in their unit price. Second, the data aggregates diverse pesticide types (e.g., herbicides, fungicides), whose application drivers may differ. Future research with more granular data could disentangle these effects. Third, our climate data is aggregated over the growing season; more precise, time-matched data on rainfall and pesticide application could offer deeper insights. These limitations notwithstanding, this paper provides a more nuanced understanding of the non-linear impact of farm size on pesticide use, offering valuable evidence for policymakers navigating the complex transition to sustainable agriculture.

Data availability statement

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding authors.

Author contributions

YY: Data curation, Funding acquisition, Writing – original draft, Writing – review & editing. XZh: Formal analysis, Visualization, Writing – review & editing. CW: Data curation, Supervision, Writing – review & editing. XZa: Funding acquisition, Project administration, Supervision, Writing – review & editing. YS: Funding acquisition, Investigation, Project administration, Resources, Supervision,

Writing – review & editing. NA: Software, Supervision, Writing – review & editing.

Funding

The author(s) declare that financial support was received for the research and/or publication of this article. This study was supported by the Natural Science Foundation of the Jiangsu Higher Education Institutions of China (no. 22KJB210002), the Natural Science Foundation of Jiangsu Province in China (no. BK20220164), the Dr. Startup project of Jinling Institute of Technology (no. jit-b-202116), the Natural Science Foundation of Xinjiang (no. 2021D01A8081), Xinjiang Tianshan Talent Training Program (no. 2022TSYCCX0093), and the Fundamental Research Funds for the Central University (no. 2662022JGQD006).

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.

Generative AI statement

The author(s) declare that no Gen AI was used in the creation of this manuscript.

Any alternative text (alt text) provided alongside figures in this article has been generated by Frontiers with the support of artificial intelligence and reasonable efforts have been made to ensure accuracy, including review by the authors wherever possible. If you identify any issues, please contact us.

Publisher's note

All claims expressed in this article are solely those of the authors and do not necessarily represent those of their affiliated organizations, or those of the publisher, the editors and the reviewers. Any product that may be evaluated in this article, or claim that may be made by its manufacturer, is not guaranteed or endorsed by the publisher.

References

- Adamopoulos, T., and Restuccia, D. (2014). The size distribution of farms and international productivity differences. *Am. Econ. Rev.* 104, 1667–1697. doi: 10.1257/aer.104.6.1667
- Akamin, A., Bidogeza, J., Rene, M. J., and Afari-Sefa, V. (2017). Efficiency and productivity analysis of vegetable farming within root and tuber-based systems in the humid tropics of Cameroon. *J. Integr. Agric.* 16, 1865–1873. doi: 10.1016/S2095-3119(17)61662-9
- Ali, D. A., and Deininger, K. (2015). Is there a farm size-productivity relationship in African agriculture? Evidence from Rwanda. *Land Econ.* 91, 317–343. doi: 10.3368/le.91.2.317
- Beddington, J. (2010). Food security, contributions from science to a new and greener revolution. *Philos. Trans. R. Soc. Lond. B Biol. Sci.* 365, 61–71. doi: 10.1098/rstb.2009.0201
- Bu, Y., Kong, Y., Zhi, Y., Wang, J., and Shan, Z. (2014). Pollution of chemical pesticides on environment and suggestion for prevention and control countermeasures. *Rev. China Agric. Sci. Technol.* 16, 19–25. doi: 10.13304/j.nykjdb.2014.129
- Cai, D. (2008). Understand the role of chemical pesticides and prevent misuses of chemical pesticides. *Bull. Agric. Sci. Technol.* 1, 36–38.
- Chen, C., and McCarl, B. (2001). An investigation of the relationship between chemical pesticide usage and climate change. *Clim. Chang.* 50, 475–487. doi: 10.1023/a:1010655503471
- Cui, Z., Zhang, H., Chen, X., Zhang, C., Ma, W., Huang, C., et al. (2018). Pursuing sustainable productivity with millions of smallholder farmers. *Nature* 555, 363–366. doi: 10.1038/nature25785
- Delcour, I., Spanoghe, P., and Uyttendaele, M. (2015). Literature review: impact of climate change on chemical pesticide use. *Food Res. Int.* 68, 7–15. doi: 10.1016/j.foodres.2014.09.030
- Fan, S., and Connie, C. K. (2005). Is small beautiful? Farm size, productivity, and poverty in Asian agriculture. *Agric. Econ.* 32, 135–146. doi: 10.1111/j.0169-5150.2004.00019.x

- Food and Agriculture Organization of the United Nations (2018). FAO Production Yearbook Scientech Documentation and Information Center of the Chinese Academy of Agricultural Science Beijing.
- Gao, J., Gai, Q., Liu, B., and Shi, Q. (2021). Farm size and pesticide use: evidence from agricultural production in China. *China Agric. Econ. Rev.* 13, 912–929. doi: 10.1108/CAER-11-2020-0279
- Ge, J., and Zhou, S. (2012). Whether the factor market distortion triggered agricultural non-point source pollution-take fertilizer as an example. *Issues Agric. Econ.* 33, 92–98. doi: 10.13246/j.cnki.iae.2012.03.001
- Henderson, H. (2015). Considering technical and allocative efficiency in the inverse farm size-productivity relationship. *J. Agric. Econ.* 66, 442–469. doi: 10.1111/1477-9552.12086
- Hu, L., Zhang, X., and Zhou, Y. (2019). Farm size and fertilizer sustainable use: an empirical study in Jiangsu, China. *J. Integr. Agric.* 18, 2898–2909. doi: 10.1016/S2095-3119(19)62732-2
- Huang, J., and Ding, J. (2016). Institutional innovation and policy support to facilitate small-scale farming transformation in China. *Agric. Econ.* 47, 227–237. doi: 10.1111/agec.12309
- Jin, J., Wang, W., He, R., and Gong, H. (2017). Chemical pesticide use and risk perceptions among small-scale farmers in Anqiu County, China. *Int. J. Environ. Res. Public Health* 14:29. doi: 10.3390/ijerph14010029
- Ju, X., Gu, B., Wu, Y., and Galloway, J. (2016). Reducing China's fertilizer use by increasing farm size. *Glob. Environ. Chang.* 41, 26–32. doi: 10.1016/j.gloenvcha.2016.08.005
- Kavlock, R. J., Daston, G. P., Derosa, C., Fenner-Crisp, P., Earl, G. L., Kaattari, S., et al. (1996). Research needs for the risk assessment of health and environmental effects of endocrine disruptors: a report of the USEPA-sponsored workshop. *Environ. Health Perspect.* 104, 715–740. doi: 10.1289/ehp.96104s4715
- Larson, D. F., Otsuka, K., Matsumoto, T., and Kilic, T. (2012). Should African rural development strategies depend on smallholder farms? An exploration of the inverse productivity hypothesis. *Agric. Econ.* 45, 355–367. doi: 10.1111/agec.12070
- Lau, L. J., and Yotopoulos, P. A. (1971). A test for relative efficiency and application to Indian agriculture. *Am. Econ. Rev.* 61, 94–109. doi: 10.2307/1910544
- Li, H., Zeng, E., and You, J. (2014). Mitigating chemical pesticide pollution in China requires law enforcement, farmer training, and technological innovation. *Environ. Toxicol. Chem.* 33, 963–971. doi: 10.1002/etc.2549
- Maor, M. (2019). Climate change exacerbates pest damage through reduced chemical pesticide efficacy. *Pest Manag. Sci.* 75, 9–13. doi: 10.1002/ps.5121
- Ministry of Agriculture and Rural Affairs of the People's Republic of China (MOARA) (2015). Zero growth in pesticide use by 2020. Available online at: http://www.moa.gov.cn/nybgb/2015/san/201711/t20171129_5923401.htm
- Popp, J., Peto, K., and Nagy, J. (2013). Chemical pesticide productivity and food security: a review. *Agron. Sustain. Dev.* 33, 242–255. doi: 10.1007/s13593-012-0105-x
- Rahman, S. (2013). Chemical pesticide consumption and productivity and the potential of IPM in Bangladesh. *Sci. Total Environ.* 445, 48–56. doi: 10.1016/j.scitotenv.2012.12.032
- Ren, C., Liu, S., van Grinsven, H., Reis, S., Jin, S., Liu, H., et al. (2019). The impact of farm size on agricultural sustainability. *J. Clean. Prod.* 220, 357–367. doi: 10.1016/j.jclepro.2019.02.151
- Sheng, Y., Ding, J., and Huang, J. (2019). The relationship between farm size and productivity in agriculture: evidence from maize production in northern China. *Am. J. Agric. Econ.* 101, 790–806. doi: 10.1093/ajae/aay104
- Sparks, D. L. (2001). Elucidating the fundamental chemistry of soils: past and recent achievements and future frontiers. *Geoderma* 100, 303–319. doi: 10.1016/S0016-7061(01)00026-x
- Valenciano, J. B., Casquero, P. A., Boto, J. A., and Guerra, M. (2005). Effect of sowing techniques and seed chemical pesticide application on dry bean yield and harvest components. *Field Crop Res.* 96, 2–12. doi: 10.1016/j.fcr.2005.04.016
- Wang, J., Li, Y., Wang, X., and Wang, Y. (2017). Status quo of chemical pesticide use in China and its outlook. *Agric. Outlook* 2, 56–60. doi: 10.3969/j.issn.1673-3908.2017.02.012
- Wu, Y., Xi, X., Tang, X., Luo, D., Gu, B. J., Lam, S. K., et al. (2018). Policy distortions, farm size, and the overuse of agricultural chemicals in China. *Proc. Natl. Acad. Sci. U.S.A.* 115, 7010–7015. doi: 10.1073/pnas.1806645115
- Xu, Z. (2020). Farm size, capitalism, and overuse of agricultural chemical in China. *Capitalism Nat. Soc.* 31, 1–16. doi: 10.1080/10455752.2019.1675736
- Yi, F., Sun, D., and Zhou, Y. (2015). Grain subsidy, liquidity constraints and food security-impact of the grain subsidy program on the grain-sown areas in China. *Food Policy* 50, 114–124. doi: 10.1016/j.foodpol.2014.10.009
- Yin, J., and Yu, G. (2019). The difference and influencing factors of the demand for agricultural technology service of the small scale farm land and peasant household. *Chin. J. Agric. Resour. Reg. Plan.* 40, 93–100. doi: 10.7621/cjarrp.1005-9121.20191012
- Yuan, Y., and Zhang, X. (2021). Comparison of agrochemicals allocation efficiency between greenhouse and open-field vegetables in China. *Sci. Rep.* 11:12807. doi: 10.1038/s41598-021-92316-7
- Zhang, C., Hu, R., Shi, G., Jin, Y., Robson, M. G., and Huang, X. (2015). Overuse or under use? An observation of chemical pesticide use in China. *Sci. Total Environ.* 538, 1–6. doi: 10.1016/j.scitotenv.2015.08.031
- Zhang, X., Hu, L., and Yu, X. (2023b). Farmland leasing, misallocation reduction, and agricultural total factor productivity: insights from rice production in China. *Food Policy* 119:102518. doi: 10.1016/j.foodpol.2023.102518
- Zhang, W., Jiang, F., and Ou, J. (2011). "Global chemical pesticide consumption and pollution: with China as a focus." in *Proceedings of the International Academy of Ecology and Environmental Sciences*. pp. 1, 125–144.
- Zhang, H., and Lu, Y. (2007). End-users' knowledge, attitude, and behavior towards safe use of chemical pesticides, a case study in the Guanting reservoir area, China. *Environ. Geochem. Health* 29, 513–520. doi: 10.1007/s10653-007-9120-2
- Zhang, X., Ma, W., Vatsa, P., and Jiang, S. (2023a). Short supply chain, technical efficiency, and technological change: insights from cucumber production. *Agribusiness* 39, 371–386. doi: 10.1002/agr.21789
- Zhang, X., and Yu, X. (2021). Short supply chain participation, and agrochemicals' use intensity and efficiency: evidence from vegetable farms in China. *China Agr. Econ. Rev.* 13, 721–735. doi: 10.1108/CAER-05-2020-0108
- Zhang, X., Yu, X., Tian, X., Geng, X., and Zhou, Y. (2019). Farm size, inefficiency, and rice production cost in China. *J. Prod. Anal.* 52, 57–68. doi: 10.1007/s11123-019-00557-6
- Zhang, X., Yu, X., Tian, X., Geng, X., and Zhou, Y. (2017). Farm size and rice production cost: a case study in Jiangsu. *Issues Agric. Econ.* 2, 48–54. doi: 10.13246/j.cnki.iae.2017.02.007