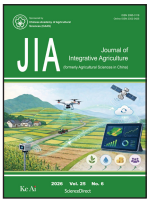
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RESEARCH ARTICLE

Does the usage of online agricultural information reduce agrochemical expenses in China?

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Highlights

- Online agricultural information increases agrochemical spending among Chinese family farms, particularly among smallholders.
- Poor information quality limits the potential sustainability gains of online agricultural information.
- Education and digital literacy are key to increasing the positive potential of digital information.

Abstract

Motivated by growing concerns about excessive agrochemical use and the resulting environmental pollution in China, this study explores the importance of online agricultural information for chemical fertilizer and pesticide use decisions among grain farmers. In particular, we focus on the functional agricultural information used for productive purposes for smallholders. Based on a survey dataset of 1,833 family farms across five Chinese provinces, we employ a propensity score matching (PSM) approach to estimate treatment effects of online agricultural information. The results reveal that online acquisition of agricultural information does not reduce the expenses of chemical fertilizers and pesticides in our sample; rather, the opposite is true. The use of online agricultural information significantly increased agrochemical expenses, particularly among smallholders. Within our sample region, the limited evolution of online information content and the inherent challenges faced by smallholder farmers are the major barriers to the beneficial effects of online agricultural information in reducing agrochemical use. Our findings emphasize the need for targeted interventions and educational efforts to bridge the knowledge gaps of smallholders. Furthermore, there is a need to raise awareness among information providers to ensure that their recommendations avoid encouraging overdoses of agrochemicals. In addition, enhancing farmers' digital literacy will be a future task of development policy.

Keywords: digitalization, propensity score matching, sustainability, chemical fertilizer, pesticides

1. Introduction

Chemical fertilizers and pesticides, two of the most important production inputs in agriculture, play essential roles in increasing agricultural yields (Wood *et al.* 1993) and in preventing crop diseases and pests (Cooper and Dobson 2007). However, the inappropriate and excessive use of agrochemicals has also caused many problems, including food safety concerns, greenhouse gas emissions, and water and soil pollution, thereby threatening worldwide sustainable agricultural development (Pimentel *et al.* 1992).

China has one of the highest levels of agrochemical inputs globally, even surpassing those of many developed nations. As reported by CAGDRS and IARRP (2022), China stands as the largest consumer of chemical fertilizers, with annual consumption reaching 51.91 million tons in 2021, alongside ranking as the fourth-largest consumer of pesticides, with 248,300 tons consumed in 2021. Moreover, data from *China Rural Statistical Yearbook* (NBSC 2022) indicate that the intensity of fertilizer application stands notably higher than the globally recommended safe threshold (225 kg ha^{-1}), reaching 307.7 kg ha^{-1}, whereas pesticide application intensity was recorded at 7.3 kg ha^{-1} in 2021. A significant portion of these agrochemicals is not effectively utilized by crops, leading to soil and water contamination and reduced food safety. The

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prevalent high-volume and excessive application of these agrochemicals, particularly among smallholders, has led to inefficiencies and severe non-point pollution (Ye and Rozelle 1994). In response to these challenges, China's Ministry of Agriculture initiated two actions in 2015, seeking zero growth in chemical fertilizer and pesticide use by 2020 (MOA 2015) and then extended the actions in 2022 as another five-year development goal to further reduce the agrochemical use and optimize the use structure of fertilizer and pesticide (MARA 2022). Despite efforts to curb consumption, agrochemical use has declined over eight consecutive years, yet absolute consumption values remain high. At the same time, the utility efficiency of both chemical fertilizers and pesticides remains comparatively low, standing at 40.2 and 40.6%, respectively, in 2020 (MARA 2021). Research demonstrates that small farm size in China is strongly related to the overuse of agricultural chemicals (Wu *et al.* 2018; Ren *et al.* 2021). A lack of awareness and knowledge in the scientific utilization of agrochemical inputs, especially among smallholders, is one major hindering factor (Wilson and Tisdell 2001; Liu and Huang 2013).

The expansion of informatization and digitalization offers a promising solution to facilitate sustainable agricultural development (Deichmann *et al.* 2016). The spread of mobile Internet and the rising Internet users improve access to agricultural extension services and information about agrochemical use (Aker 2011). This information further contributed to the agro-food sustainability transition by improving the efficiency of resource and input use (Fu and Akter 2016; El Bilali and Allahyari 2018). By 2022, the number of rural Internet users in China had reached 284 million, and the Internet penetration rate in rural areas was 58.8% (CINIC 2022). As the scale of rural Internet users continues to expand, the Internet has rapidly penetrated China's rural areas with its unique advantages, such as breaking through time and space constraints, reducing information asymmetry, and being low-cost (Su and Kong 2020). Online information is increasingly incorporated into farmers' production decisions (Yin *et al.* 2023). However, the ability to access, process, and use online information varies among farmers. Large-scale professional farmers with specialized expertise encounter fewer impediments in integrating online agricultural information into their agricultural operations (Gao *et al.* 2020). Conversely, smallholders, characterized by comparatively lower educational attainment, may face challenges embracing digital agricultural practices (Gong *et al.* 2016).

A growing body of literature focuses on informatization and digitalization in China's agriculture. Particularly in fertilizer and pesticide use, studies have explored the effects of information technology interventions on expenditure (Ma and Zheng 2022; Na and Kang 2023), reduction (Zhao *et al.* 2021; Yin *et al.* 2023), and efficiency (Bai *et al.* 2019; Zhu *et al.* 2023). Existing studies often focus on general Internet or smartphone access, without addressing the critical distinction between device possession and the active use of agricultural information for decision-making. In this light, our study aims to shed further light on how crop farmers' engagement with professional agricultural information on the Internet specifically influences their agrochemical use decisions, from the perspectives of unit monetary input and application frequency. Specifically, we want to answer the following research questions: What role does online agricultural information play in shaping crop farmers' use of chemical fertilizers and pesticides, particularly in the context of smallholders, the predominant farmer type in China?

Our research contributes empirical evidence on the impact of online information on the input allocation decisions of smallholders, who particularly need improved knowledge of the efficient use of fertilizer and pesticides. Recent studies have shown that Chinese smallholder farmers often overuse agrochemicals, largely due to limited access to fixed inputs and technical guidance, leading them to rely on excessive fertilizer application to secure yields (Ren *et al.* 2021). Our specified sub-sample analysis contributes to understanding the factors behind agrochemical usage among smallholders (Kaila and Tarp 2019; Ma and Zheng 2022). We find that online agricultural information use is associated with increased farmers' agrochemical use. We provide a thorough discussion on the potential reasons for the counterintuitive findings by exploring and interpreting the unique characteristics of smallholders. The observed insufficiency of tailored agricultural information highlights the need to adjust online extension services to the needs and capabilities of smallholders. Given that the overwhelming majority of farms in China are still small family farms, sustainable resource use can only be achieved in partnership with smallholder farmers.

2. Conceptual framework

2.1. Influence mechanism of the Internet on farmers' production behavior

Existing research analyzed the transformative influences of the Internet on farmers' production behavior. In Fig. 1, we summarize common transmission approaches across diverse online information content, their potential influence on farmers' behavior, and their implications for production activities. The Internet serves as a dynamic and flexible platform, transcending temporal and geographical constraints, thereby enhancing users' ability to collect and use information effectively (Baourakis *et al.* 2002). Compared to traditional channels, it provides farmers with more flexible access to information on agricultural production, offering the latest research, best practices, and success stories in pesticide and fertilizer management. This not only broadens their information access but also strengthens their overall information-seeking capacity (Yan and Zheng 2021). Moreover, the Internet plays a significant role in guiding farmers' production decisions. It facilitates precision agriculture techniques, allowing farmers to apply pesticides and fertilizers precisely where needed, minimizing overuse and optimizing resource utilization (Zhao *et al.* 2021).

Additionally, the Internet acts as an educational platform, enhancing farmers' environmental awareness by providing information on the adverse effects of pesticide and fertilizer use on human health and the environment (Sharma *et al.* 2012; Peng *et al.* 2019; Ha *et al.* 2022). Through online information, farmers aim to optimize pesticide and fertilizer

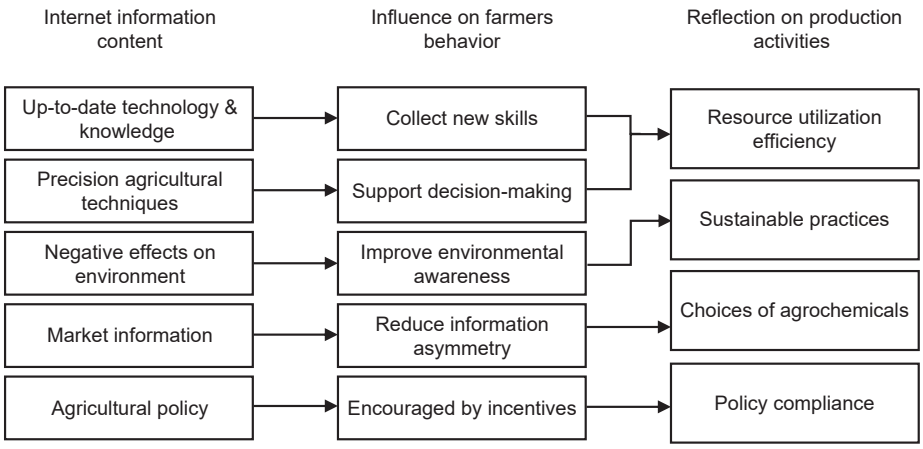


Fig. 1 Transmission mechanism of online agricultural information on production behavior. Source: Own illustration

use in alignment with sustainable and environmentally friendly farming practices (Wang and Hao 2018).

Furthermore, the Internet is a powerful tool for reducing information asymmetry among various stakeholders, including farmers, consumers, and suppliers (Asongu *et al.* 2019; Ullah *et al.* 2020; Zhu and Song 2020). Updated online information on market prices and demand significantly influences economic incentives related to specific pesticides and fertilizers, thereby shaping farmers' input decisions (Jin *et al.* 2015).

Lastly, online information serves as guidelines for farmers to stay informed about agricultural policies and regulations related to pesticide and fertilizer use (Zhang *et al.* 2019). It facilitates compliance with environmental standards and encourages sustainable farming practices (Gonel and Akinci 2018). The dynamic interplay between government policies promoting sustainability and farmers' responses shapes patterns of pesticide and fertilizer use, highlighting the complex relationship between policy frameworks and on-the-ground agricultural practices.

2.2. Relation between information technology and the usage of chemical fertilizers and pesticides

Existing literature has investigated the relationship between information technology adoption and pesticide and fertilizer usage, revealing diverse regional patterns.

Certain research evidence showed that the adoption of information technology increases the agrochemical inputs (Cole and Fernando 2012; Ogutu *et al.* 2014; Rajkhowa and Qaim 2021; Na and Kang 2023). In India, Cole and Fernando (2012) found a significant increase in pesticide and fertilizer use in cotton cultivation with the adoption of mobile phones. Similarly, Rajkhowa and Qaim (2021) demonstrated in India that personalized digital extension services are positively associated with input intensity. Ogutu *et al.* (2014) observed increased fertilizer purchases with the use of ICT-based market information services in Kenya. Na and Kang (2023) highlighted that farmers who use the Internet exhibit greater use of fertilizers and pesticides than non-users. The given reasons are (1) farmers use the Internet to access farming practices, but this action does not enhance their environmental awareness; (2) farmers increased their pesticide purchases through online shopping, which in turn increased fertilizer and pesticide expenditures. However, these findings lack a comprehensive discussion or supporting empirical evidence.

By contrast, various case studies offered contradictory insights (Yuan *et al.* 2021; Zhao *et al.* 2021; Yin *et al.* 2023; Zeng 2023). Based on a nationwide dataset of 7,766 households, Yuan *et al.* (2021) found that Internet use in China enhanced farmers' human capital, leading to reduced chemical fertilizer use. Zhao *et al.* (2021) found that both the frequency of Internet use and the number of Internet activities are associated with pesticide reduction among vegetable farmers. Yin *et al.* (2023) emphasized that Internet embedding effectively promotes the reduction of chemical pesticides across diverse farming models in China. Zeng (2023)'s study focused on professional farmers in China, highlighting a varied adoption rate of green technology, with professionals exhibiting a higher rate than the overall agricultural sector. It also revealed the digital divide between generally conservative-minded smallholders and professional farmers.

Lastly, some studies found a mixed relationship between information technology and chemical fertilizer and pesticide usage (Al-Hassan 2013; Freeman and Qin 2020; Ma and Zheng 2022). Al-Hassan *et al.* (2013) found that ICT-based project participation increased pesticide expenditure in Ghana but decreased fertilizer expenditure. Freeman and Qin (2020) noted a positive but insignificant impact of mobile phone access on fertilizer use in Uganda, coupled with a significant increase in pesticide use. Ma and Zheng (2022) found heterogeneous effects of smartphone use on pesticide and fertilizer expenditures in China. Their results showed that smartphone use significantly increases pesticide expenditure by 33% at the lowest 20th quantile. However, general Internet use based on ICT cannot be equated with the production purpose of acquiring information, as not all smallholders are able or motivated to obtain and process the professional information offered by ICT.

In conclusion, the literature review underscores the complex, context-dependent relationships between

information technology adoption and pesticide and fertilizer use, emphasizing the need for region-specific insights and tailored interventions. Notably, very few studies have focused on crop farmers' acquisition of professional agricultural information on the Internet, instead concentrating on individual smartphone ownership or household Internet access. However, mere possession of Internet-enabled devices does not guarantee farmers' engagement with agricultural information. Individuals may use such devices for various purposes unrelated to agricultural practices, such as entertainment, social media engagement, or status symbols. Our research contributes to this gap by explicitly investigating the role and effects of Internet use specifically for agricultural purposes. We aim to provide a more precise understanding of the factors influencing farmers' decision-making processes and the adoption of sustainable agricultural practices.

3. Data and methods

3.1. Data

Our empirical analysis relies on data collected from a sample of 1,833 crop farms selected through a stratified random sampling approach across five provinces in China in summer 2022 . For the survey, our target population was household farms in central, western, and northwestern China. At the first level, we sampled five Chinese provinces representing the Sichuan Basin and surrounding regions (Sichuan), the Middle-lower Yangtze Plain (Hunan and Hubei), the Huang-Huai-Hai Plain (Henan), and the Northeastern China Plateau (Heilongjiang).

Heilongjiang, the largest grain-producing province, employs a large-scale mechanization model, with maize, rice, and soybean output ranking first in China. Henan, Hubei, and Hunan are located in central China, with diverse regional geographic conditions and a wide range of crops. It is a transitional zone from large-scale mechanized production to intensive small-scale farming, with plain terrain in the north and hilly and mountainous areas in the south. Sichuan is the only major grain-producing area in western China, characterized by a smallholder production pattern constrained by fragmented arable land.

Below the province level, we sampled counties and townships using a clustered-stratified sampling approach, selecting six counties per province and two townships per county based on agroecological background and GDP. In detail, we followed the k-means clustering method, based on indicators reflecting population, land, economy, and agricultural output. Within each township, we sampled two villages using a stratified random sampling approach, with villages sorted into two strata by average income. Within villages, 15 households were selected for interviews from a sampling frame provided by village heads through simple random sampling. In each village, we additionally sampled two to three large farms to correct for potential sampling biases due to expected lower responsiveness and response errors among larger farmers and thus avoid accidental undersampling of this (still) rare population under the simple random sampling approach.

A structured questionnaire was used to collect detailed information on socioeconomic characteristics (e.g, age, gender, and education of the main decision maker), demographic and general farm characteristics (e.g, household and farm size, total income), output and inputs (e.g, expenditures on seeds, and fertilizers, machinery use) of agricultural production, and farmers' status of technology and information adoption.

Among the total 2,395 farm household observations, 2,114 households were engaged in crop farming in 2021. From the remaining observations, 281 households were excluded due to outlier control, inconsistency, and item nonresponse. A total of 1,833 observations could be retained for our empirical analysis. Using national production statistics as a benchmark, the sample can be considered representative of each study region with respect to grain crop production and diversity of agricultural practices.

3.2. Propensity score matching (PSM)

The PSM technique provides an unbiased estimation of treatment effects and can draw causal-effect inferences in non-experimental settings (Rosenbaum and Rubin 1985). The advantage of the PSM is that it does not rely on any functional assumption about the relationship between the outcomes (agrochemical use) and its determinants (Becerril and Abdulai 2010). Further, it can account for selectivity bias (Dehejia and Wahba 2002), addressing by assuming conditional independence.

We employ the PSM method to provide an unbiased estimation of treatment effects. Based on the counterfactual analysis framework of PSM, the treatment of interest is farmers' use of smartphones to access online agricultural information. Farmers who used smartphones to access online agricultural information represent the treatment group, whereas those who did not use mobile phones to access online agricultural information are the counterfactual/control group. Formally, let D_i□{0, 1} denote the treatment indicator variable, where D_i=1 if farmer i uses online agricultural information and D_i=0 otherwise. Under the potential outcomes framework, each farmer is assumed to have two potential outcomes: $Y_i(1)$, representing agrochemical use if the farmer adopts online information, and $Y_i(0)$, representing agrochemical use in the absence of adoption. The observed outcome can therefore be written as:

$$Y_i=D_iY_i(1)+(1-D_i)Y_i(0)$$

The main parameter of interest is the average treatment effect on the treated (ATT), defined as the expected difference between these two potential outcomes for farmers who actually adopted online agricultural information:

$$ATT=E[Y_i(1)-Y_i(0)|D_i=1]$$

Since $Y_i(0)$ is unobservable for treated farmers, PSM constructs the counterfactual outcome by matching treated farmers with comparable untreated farmers who have similar observable characteristics. This is achieved through the propensity score, defined as the conditional probability of treatment given a vector of covariates X_i:

$$p(X_i)=\Pr[D_i=1|X_i]$$

Under the assumptions of conditional independence $\{Y_i(1),Y_i(0)\} \perp D_i|X_i$ and common support $0<p(X_i)<1$, the ATT

can be identified as:

$ATT=E\{E[Y_i|D_i=1, p(X_i)]-E[Y_i|D_i=0, p(X_i)]|D_i=1\}$

In practice, the propensity score is estimated using a binary response model such as logit:

$$p(X_i)=\Pr[D_i=1|X_i)=\frac{\exp(\beta X_i)}{1+exp(\beta X_i)}$$

There are different approaches to implementing the matching process in PSM, including nearest neighbor matching, caliper or radius matching, stratification and interval matching, and kernel and local linear matching (Heckman *et al.* 1998; Smith and Todd 2005; Caliendo and Kopeinig 2008). We first generated the density distribution of propensity scores for the treated and control groups. Meanwhile, balancing tests before matching and after matching were checked. In our analysis, 1:4 nearest neighbor matching (NNM), kernel matching (KM), and local linear matching (LLM) are used. The most straightforward matching estimator is nearest neighbor matching. We used more than one nearest neighbor to reduce variance, thereby providing more information for constructing the counterfactual for each participant (Smith 1997). Kernel matching and local linear matching are non-parametric matching estimators that use weighted averages of all individuals in the control group to construct the counterfactual outcome. One significant advantage is that the lower variance can be achieved by including more information. Compared to KM, LLM includes an additional linear term in the propensity score of a treated individual. It is an advantage when comparison-group observations are distributed asymmetrically around the treated observation (Caliendo and Kopeinig 2008). Finally, to guarantee representativeness at the above province level, we introduced population weights generated based on the national agricultural census.

3.3. Variables selection

Dependent variables Table 1 summarizes the variables used in the empirical analysis and presents the means and standard deviations of model variables across the whole sample as well as the treatment and control groups.

The chemical fertilizer expenditure (CNY mu^{-1}) and pesticide expenditure (CNY mu^{-1}) are used as dependent variables to explore the influence of online agricultural information (1 ha= 15 mu). In the following discussions, we use fertilizer and pesticide input terminology for simplicity throughout the text, which refers mainly to expenditures on fertilizer and pesticide in CNY mu^{-1}.They are the most commonly used of farmers' investments in agrochemical inputs. Considering the considerable variation of chemical properties of the pesticide (e.g, dose, type, and chemical composition) and their effectiveness and stability under different environmental conditions (e.g, rainfall, temperature, and soil type) across products and producers, any volume or weight measure might be biased, especially since there are substantial differences in the environmental effects between slow-release and quick-release fertilizers (Priya *et al.* 2024). Therefore, our measure analyses farmers' attitudes toward fertilizer and pesticide use, but not their precise environmental or agronomic efficiency. In the dataset, the average expenditure on chemical fertilizer among online agricultural information users is 335 CNY mu^{-1}, higher than the average input among non-users (221 CNY mu^{-1}). Regarding pesticide expenditure, the information users spent 35 CNY mu^{-1} on average, less than non-users (39 CNY mu^{-1}).

Furthermore, we use the pesticide application frequency (times) as a supplementary measure of the behavior of pesticide use. Overall, farmers who used online agricultural information applied pesticides more often (4.0 times application) than non-users (3.4 times application) in the dataset, showing a contradictory pesticide expenditure pattern. Unfortunately, the dataset does not cover the frequency of chemical fertilizer application.

Independent variable The independent variable is measured by the use of online agricultural information. In our dataset, households indicated whether they use mobile phone apps for agricultural information consulting activities, such as local weather forecasts, soil information, market conditions, and agricultural policies. If so, the value is 1; otherwise, it is 0. In the overall sample, 44.3% of farmers accessed agricultural information through mobile phones. Despite over 95% of households having access to the Internet, only half linked their online activities to agricultural production.

Control variables For determinants of information and technology use, previous studies pointed out that farmers' personal characteristics, household characteristics, and government training played important roles (Al-Hassan 2013; Issahaku *et al.* 2018; Mwalupaso *et al.* 2019; Ma and Zheng 2022; Yin *et al.* 2023; Zeng 2023). These factors may result in farmers having different needs and capabilities to be involved in Internet information-seeking and agrochemical use behaviors. Therefore, we select the following variables: age (age of household head), education (highest education level of household members), commercialization (sold products to market or not), information source (Internet as a primary source of learning agricultural technology and skills), and training (received training about pesticide application).

Production characteristics are also important factors affecting crop farming activities and farmers' adoption of online information (Jin *et al.* 2015; Zhao *et al.* 2021; Emileva *et al.* 2023; Kang S *et al.* 2023; Zhu *et al.* 2023). In terms of input factors, we use the following variables: Labor measures household working hours. Land is the total size of crop production (mu). Organic fertilizer refers to the use of organic fertilizer during production. Machinery is the machinery used to apply fertilizer or pesticide.

4. Results

4.1. Determinants of online agricultural information use

Prior to the PSM estimator for the ATT on agrochemical use, Table 2 examines the determinants of online agricultural information use. From the perspective of household characteristics, the younger the household head, the more likely the head is to use online agricultural information. The highest education level in the household is significantly and positively associated with farmers' use of online agricultural information. This is in line with expectations, as individuals with higher education levels have stronger abilities to learn, adopt, and spread new knowledge and technologies, and are more inclined to use the Internet. Access to the market

Table 1 Model variable's summary statistics

Variable	Description	Measurement[1)]	Mean			Diff
			Overall	Users	Non-users	
Outcome variable						
Fert. exp.	Chemical fertilizer expenditure	Mean (CNY mu^{-1})	271.20 (426.10)	335.27 (562.04)	220.91 (265.64)	114.36***
Pest. exp.	Pesticides expenditure	Mean (CNY mu^{-1})	37.58 (64.78)	35.40 (58.39)	39.30 (69.36)	–3.90
Pest. app. freq.	Pesticide application frequency	Mean (times)	3.65 (3.35)	3.95 (4.33)	3.39 (2.22)	0.56***
Independent variable						
Digital info. use	Online agricultural information use	Yes/No	0.44 (0.50)			
Control variable						
Age of HH head	Age of household head	Mean (years)	57.15 (10.14)	54.14 (9.22)	59.00 (10.09)	–4.86***
Education level	Highest education level of household members	Mean (0–7)	2.88 (1.65)	3.31 (1.68)	2.61 (1.60)	0.70***
Commercialization	Access to market	Yes/No	0.60 (0.49)	0.58 (0.49)	0.63 (0.48)	–0.05**
Internet=Primary source	Internet as a primary source of learning agricultural technology and skills	Yes/No	0.16 (0.36)	0.25 (0.43)	0.09 (0.28)	0.17***
Pesticide training	Received training about pesticide application	Yes/No	0.10 (0.30)	0.17 (0.38)	0.07 (0.26)	0.10***
Land	Land input	Mean (mu)	46.45 (130.62)	63.15 (150.38)	44.46 (126.72)	18.69***
Labor	Family labor input	Mean (hour)	11,035.13 (219,313.20)	20,017.95 (328,010.70)	4,114.25 (40,831.94)	15,903.70*
Organic fertilizer	Organic fertilizer usage	Yes/No	0.35 (0.48)	0.44 (0.50)	0.28 (0.45)	0.16***
Fertilization machinery	Machinery usage in fertilization	Yes/No	0.28 (0.45)	0.30 (0.46)	0.27 (0.44)	0.03
Pesticide machinery	Machinery usage in pesticides	Yes/No	0.25 (0.43)	0.30 (0.46)	0.21 (0.41)	0.09***

[1)] 1 ha=15 mu. Mean of education level definition: 0=no formal education, 7=postgraduates (including master & doctor).
Standard deviation in parentheses. *, P<0.10; **, P<0.05; ***, P<0.01.

is negatively associated with the use of online agricultural information. Commercial farmers are more likely to rely on information exchange through markets rather than the Internet, as their essential information (such as buyer requirements, quality standards, and market demand) is more often exchanged in market settings than through Internet sources. Finally, farmers who view the Internet as their primary source of agricultural knowledge and technology are more likely to seek online agricultural information. From the perspective of production activities, adopting organic fertilizer and using fertilization machinery are positively associated with the use of online agricultural information. However, land and family labor inputs were not significantly associated with access to online agricultural information.

Table 3 presents the logit model results with additional control variables relevant to pesticide training to address potential endogeneity arising from self-selection in information use. The newly added variable, whether or not a farmer received training about safe pesticide use, especially on application frequency and intervals, is positively associated with online agricultural information use.

4.2. Full sample analysis of online agricultural information and agrochemical use

The common support tests show successful matches between online agricultural information users and non-users. The larger the common support domain, the smaller the probability of sample loss during matching. In Fig. 2, only a few observations are outside the common value range. Therefore, the common support criterion of the propensity score matching technique has been met.

A balance test is used to assess whether the treated (farmers who use online agricultural information) and control (non-users) groups have comparable characteristics. We

Table 2 Logit model estimates (chemical fertilizer)

Variable	Logit	Marginal effect
Age of HH head	–0.039 (0.01)***	–0.008 (0.00)***
Education level	0.169 (0.08)***	0.036 (0.01)***
Commercialization	–0.191 (0.33)*	–0.040 (0.02)*
Internet=Primary source	1.285 (0.41)***	0.272 (0.03)***
Land	0.000 (0.00)	0.000 (0.00)
Labor	0.000 (0.00)	0.000 (0.00)
Organic fertilizer	0.623 (0.28)***	0.132 (0.02)***
Fertilization machinery	0.251 (0.42)**	0.053 (0.03)***
Constant	1.107 (0.87)***	
LR chi^2	311.94	
Pseudo R^2	0.00	
Number of observations	2,042	

Standard errors in parentheses. *, P<0.10; **, P<0.05; ***, P<0.01.

find that the pseudo R-square and the likelihood ratio Chi-square for both models dropped significantly after matching. Table 4 shows that matching significantly reduces the level of characteristic bias of the treated and control groups (Issahaku *et al.* 2018). Rosenbaum and Rubin (1985) recommended that a reduction in bias greater than 20% implies a sufficient matching quality. Both the mean and median standard biases decreased by over 20%, indicating reliable matching. The significance test of the probability value changed from highly significant to insignificant. These decreasing trends indicate that the matching procedures produce a better balance in all three models.

In the sensitivity analysis for hidden bias, the gamma estimates indicate the critical levels of the treatment effects in Table 4. In order to test the sensitivity of the matching results to unobservable factors, we employed the Rosenbaum bounding approach (Rosenbaum 2002). The results indicate that the impact of unobservable factors is not sensitive to the estimation, and the estimates are relatively reliable.

Table 5 reports the ATTs of online agricultural information on farmers' agrochemical use. Within the full sample, farmers who used online agricultural information had higher fertilizer expenditures by 79–100 CNY mu^{-1} (ca. 166–211 USD ha^{-1}) and applied pesticides more frequently by 0.4 times, respectively. However, online agricultural information did not significantly affect pesticide expenditure. It shows an insignificant decrease of 4–5 CNY mu^{-1} (ca. 9–10 USD ha^{-1}).

Table 3 Logit model estimates (pesticide)

Variable	Logit	Marginal effect
Age of HH head	–0.039 (0.01)***	–0.008 (0.00)***
Education level	0.167 (0.04)***	0.035 (0.01)***
Commercialization	–0.276 (0.12)***	–0.058 (0.02)***
Internet=Primary source	1.279 (0.20)***	0.271 (0.03)***
Pesticide training	0.769 (0.17)***	0.163 (0.03)***
Land	–0.000 (0.00)	–0.000 (0.00)
Labor	0.000 (0.00)	0.000 (0.00)
Pesticide machinery	0.368 (0.16)***	0.078 (0.03)***
Constant	1.306 (0.40)***	
LR chi^2	311.13	
Pseudo R^2	0.111	
Number of observations	2,042	

Standard errors in parentheses. *, P<0.10; **, P<0.05; ***, P<0.01.

4.3. Sub-sample analysis of online agricultural information and agrochemical use

Farming in China is still characterized by a large number of smallholder farmers. Smallholders are typically characterized by individual properties pertaining to cognitive abilities, attitudes, and educational attainments, not all of which can be controlled by our survey data. These latent characteristics might not only affect farmers' ability and interest in using online information at all, but also their processing and utilization of agricultural information.

To address this, we conducted a sub-sample analysis among farms with less than 100 mu (6.67 ha) of cultivated land in 2021, a commonly used threshold in Chinese agricultural studies to define smallholder farms (MOA 2014). This reflects the typical scale of family farming operations in rural areas and aligns with classifications from previous research (Sheng *et al.* 2019; Li *et al.* 2023; Zhang and Wu 2024). The sub-sample represents 89.8% of the total sample (1,647 households). This analysis allows us to examine the behaviors and challenges of smallholders and tailor insights to inform policies aimed at improving their use of digital agricultural resources.

Fig. 3 show that for nearly every corresponding treated farmer within the common support, there is at least one untreated farmer. Table 6 presents covariate balancing tests and sensitivity analyses, which support the matching quality and robustness.

The sub-sample analysis is largely consistent with the findings from the full sample. Meanwhile, compared to the full sample, smallholders are highly associated with the use of chemical fertilizer. We find that smallholders who used online agricultural information spent significantly more on chemical fertilizer, by 126–134 CNY mu^{-1} (268–284 USD ha^{-1}), and applied pesticides more frequently, by 0.5 times, compared to farmers who did not use online agricultural information. The results for pesticide expenditure remained insignificant, as in the full sample.

5. Discussion

In this study, we empirically analyze how online agricultural information affects the use of chemical fertilizers and pesticides, using survey data from 1,833 grain farmers across

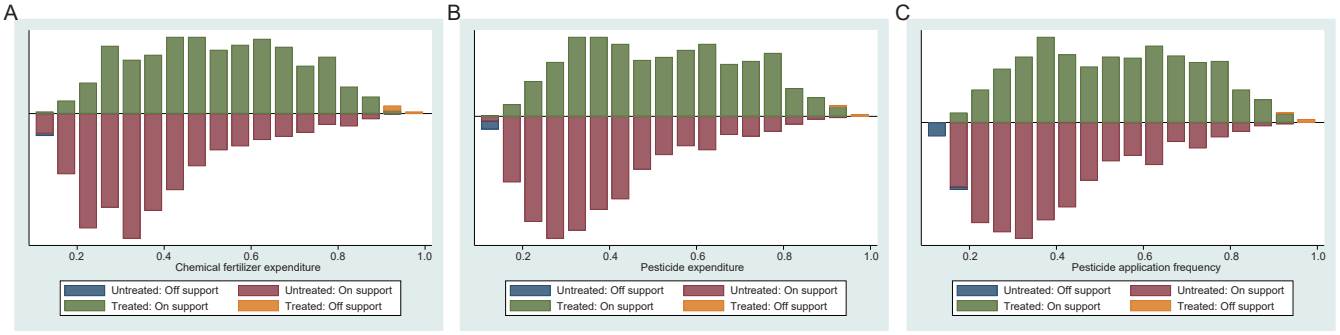


Fig. 2 Distribution of propensity scores (nearest neighbor matching (NNM), full sample). A, fertilizer expenditure. B, pesticide expenditure. C, pesticide application frequency.

Table 4 Covariate balancing tests and sensitivity analysis (full sample)

Matching method[1)]	Pseudo R^2	LR chi^2	*P*-value	Mean standard bias (%)	Median standard bias (%)	Critical Γ[2)]
Chemical fertilizer expenditure						
Before matching	0.109	274.01	0.000	26.3	24.0	
NNM	0.003	7.48	0.486	4.2	4.5	2.5–2.6
KM	0.002	5.30	0.725	3.1	2.7	3.1–3.2
LLM	0.003	6.71	0.568	4.1	3.8	3.2–3.3
Pesticide expenditure						
Before matching	0.111	279.02	0.000	28.3	27.1	
NNM	0.004	8.26	0.409	4.4	4.2	2.1–2.2
KM	0.003	6.91	0.546	4.0	3.2	2.1–2.2
LLM	0.003	5.97	0.651	3.8	2.7	2.1–2.2
Pesticide application frequency						
Before matching	0.112	258.47	0.000	28.0	26.0	
NNM	0.004	8.66	0.371	4.8	5.7	1.8–1.9
KM	0.003	5.94	0.654	4.0	3.3	2.0–2.1
LLM	0.009	18.27	0.019	6.1	4.3	1.9–2.0

[1)] NNM, nearest neighbor matching; KM, kernel matching; LLM, local linear matching.
[2)] sensitivity parameter.

Table 5 Average treatment effect on the treated (ATT) results (full sample)

Matching method[1)]	Treated households	Control households	Diff.	*t*-stat
Chemical fertilizer expenditure	*N*=815	*N*=1,018		
NNM	336.56	257.77	78.79***	3.26
KM	336.56	237.55	99.01***	4.35
LLM	336.56	236.84	99.71***	3.54
Pesticide expenditure	*N*=815	*N*=1,018		
NNM	35.68	40.64	–4.96	–1.22
KM	35.68	39.96	–4.28	–1.18
LLM	35.68	39.85	–4.18	–0.87
Pesticide application frequency	*N*=763	*N*=908		
NNM	3.97	3.56	0.41**	2.09
KM	3.97	3.55	0.42**	2.24
LLM	3.97	3.54	0.43*	1.85

[1)] NNM, nearest neighbor matching; KM, kernel matching; LLM, local linear matching.
*, *P*<0.10; **, *P*<0.05; ***, *P*<0.01.

five provinces of China. The results from a PSM analysis indicate that farmers who used online agricultural information had higher fertilizer expenditures by 79 CNY mu^{-1} (166 USD ha^{-1}) and applied pesticides 0.4 times more frequently than those who did not. Meanwhile, online agricultural information was not associated with significantly higher pesticide expenditure. As agrochemical overuse is predominantly a phenomenon of the (dominating) smallholder structure in China, we further focused our analysis on farm sized less than 100 mu (i.e., 6.67 ha). We find that small farmers who used online information for agricultural production purposes spent significantly more on chemical fertilizer, by 135 CNY mu^{-1} (284 USD ha^{-1}), and applied pesticides more frequently, by 0.5 times, than those who did not use such information. Notably, for expenditures on chemical fertilizer, the differences between treated and control smallholders are nearly twice as large as those in the full sample. Within the PSM, this analysis already takes into account inherent different of users and nonusers with respect to various farmlevel and individual characteristica.

These findings imply that farmers' internet-based information acquisition is associated with higher agrichemical use, assuming that agrichemical expenditure is positively correlated with the amount of active components applied. While these results seem counterintuitive, they are consistent with previous research, for instance with Na and Kang (2023), who showed that Internet-accessed farmers tend to have higher levels of fertilizer and pesticide inputs than non-users. One potential explanation could be the catch-up effects of smallholders. However, as shown in Appendix A in the supplementary material, smallholders generally apply more agrochemicals than large-scale farmers, spending 120 CNY mu^{-1} more on chemical fertilizers and 16 CNY mu^{-1} more on pesticides. Even among farmers who do not use online agricultural information, as indicated in Appendix B, smallholders still spend more on agrochemicals — 36 CNY mu^{-1} more on fertilizers and 19 CNY mu^{-1} more on pesticides compared to larger farms. In other words, smallholders already have higher agrochemical input levels than larger farms to start with (when untreated). This excludes the possibility of a catch-up being responsible for the observed effects. Instead, it seems that smallholders, despite already using more inputs than large farmers, are further incentivized by online agricultural information to increase their high agrochemical use. One possible explanation for the inconsistent findings across existing studies is the variation in the types of online agricultural information analyzed. For instance, Na and Kang (2023) focused on price and subsidy-related information, Zhao *et al.* (2021) examined technical guidance on pesticide use, and Zhu *et al.* (2023) analyzed weather alerts and digital tools for optimizing fertilizer applications. It can be assumed that there a considerable differences in the effectiveness of these different information types in bringing about behavioral change of farmers.

Another plausible explanation for our finding is the apparent mismatch between the demand and supply sides of agricultural information.

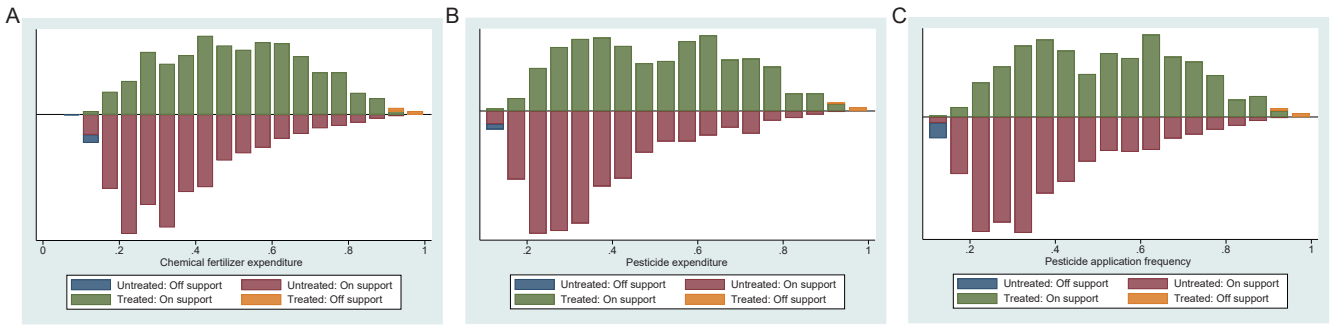


Fig. 3 Distribution of propensity scores (NNM, smallholder). A, fertilizer expenditure. B, pesticide expenditure. C, pesticide application frequency.

Table 6 Covariate balancing tests and sensitivity analysis (smallholder)

Matching method[1)]	Pseudo R^2	LR chi^2	*P*-value	Mean standard bias (%)	Median standard bias (%)	Critical Γ[2)]
Chemical fertilizer expenditure						
Before matching	0.106	244.33	0.000	24.7	25.3	
NNM	0.003	6.61	0.579	4.8	5.1	2.2–2.3
KM	0.003	5.53	0.699	3.6	3.7	3.9–4.0
LLM	0.003	6.32	0.612	4.6	4.4	3.9–4.0
Pesticide expenditure						
Before matching	0.111	235.19	0.000	28.3	24.4	
NNM	0.005	8.55	0.381	4.4	2.6	2.8–2.9
KM	0.003	5.61	0.691	3.2	2.0	3.1–3.2
LLM	0.006	10.23	0.249	4.9	3.4	3.2–3.3
Pesticide application frequency						
Before matching	0.112	216.82	0.000	28	24.6	
NNM	0.006	9.84	0.276	4.2	3.5	2.0–2.1
KM	0.002	4.06	0.852	2.6	1.4	2.0–2.1
LLM	0.007	11.17	0.192	4.1	3.2	2.0–2.1

[1)] NNM, nearest neighbor matching; KM, kernel matching; LLM, local linear matching.
[2)] sensitivity parameter.

Table 7 Average treatment effect on the treated (ATT) results (smallholder)

Matching method[1)]	Treated households	Control households	Diff	*t*-stat
Chemical fertilizer expenditure	*N*=721	*N*=962		
NNM	403.45	268.96	134.49**	2.07
KM	403.45	275.91	127.54**	2.36
LLM	403.45	276.67	126.78***	3.19
Pesticide expenditure	*N*=662	*N*=891		
NNM	37.96	43.76	–5.80	–1.31
KM	37.96	41.89	–3.93	–0.96
LLM	37.96	42.15	–4.20	–0.75
Pesticide application frequency	*N*=624	*N*=793		
NNM	4.06	3.61	0.45*	1.89
KM	4.06	3.53	0.53***	2.27
LLM	4.06	3.53	0.53*	1.92

[1)] NNM, nearest neighbor matching; KM, kernel matching; LLM, local linear matching.
*, $P<0.10$; **, $P<0.05$; ***, $P<0.01$.

Firstly, there seems to be a mismatch regarding the nature of the information available to users. Much of the current agricultural information content on the Internet originates from agrochemical producers and sellers, with much content merely serving as an advertisement (Kaila and Tarp 2019; Sun *et al.* 2021). Most farmers obtain extension information from input suppliers, who have an obvious vested interest in high agrochemical application rates (Jin *et al.* 2015; Li *et al.* 2022). The fit between official or scientific regional recommendations (if existent) and this suggested dosage, meanwhile, is neither clear nor necessarily monitored. At the end of the day, biased online information may inadvertently encourage excessive use of agrochemicals but fail to guide effective and efficient agrochemical use.

Second, available in-depth information might not be accessible for farmers. Even though government and research institutions promote scientific information online, the presentation and content of this information is likely to not fit the needs of smallholders (Cruz *et al.* 2022; Rust *et al.* 2022). Much of scientific information is presented in a manner that individuals with lower levels of education may struggle to comprehend. Here, we have to keep in mind the average digital literacy among smallholders, with 28% of surveyed farmers not using the Internet at all. Even among Internet users, 27% are unable to search for information in a browser, 40% are unable to manage mobile apps, and over 50% feel incapable of making online purchases, according to our survey data. This lack of digital know-how is the primary barrier to Internet adoption for 50% of non-users, highlighting the need for targeted digital literacy efforts (ITU 2021). Moreover, cutting-edge information is typically targeted at and limited to pilot cooperatives or large-scale professional farms, excluding smallholders. Additionally, some smallholders stated a lack of accessible online information tailored to local needs, leading to suboptimal outcomes when they attempt to follow suggested agrochemical usage guidelines (Nikam *et al.* 2022). This mismatch may result in minimal improvements in output or even adverse effects on agricultural production.

Third, factors like the low level of formal education and low digital literacy prevent accurate selection, perception, and processing of available information on the side of end

users (Pesci *et al.* 2023; Li *et al.* 2024). Evidence from a series of qualitative interviews reveals that smallholders have a relatively lower capability to access and critically assess online information. Most of them reported to passively receive and adopt information from social media communities or e-commerce platforms, but paid little attention to evaluating its sources and quality. Similarly, this lack of digital literature and general education levels hinders the selection of suitable information from the vast array of offerings provided by online sources. Hence, even when the correct information is accessible online, smallholders often encounter challenges in translating it into appropriate and desired production behaviors, leading to misinterpretation and misuse. This finding is likely to be generalizable to the whole of China, where the majority of farmers are smallholders, for whom a lack of formal education and low levels of information use are symptomatic.

Fourth, smallholders on average have more conservative mindsets and are more risk-averse than the general population (Binswanger and Sillers 1983), which may also lead them to approach online information with a more cautious attitude (Menapace *et al.* 2013). Instead, they often rely on the traditional production experience and methods passed down through generations (Rust *et al.* 2022). Online information might be distrusted due to its varying content and quality, and the lack of true expert knowledge of the content creator. Especially vulnerable smallholders will tend to avoid potential risks coming with the introduction of novel information and technologies.

Finally, there might be a fundamental mismatch of motivation: Given moderate agrochemical prices due to subsidization and still comparatively low regulatory pressure towards sustainable use of agrochemical in most Chinese provinces, farmers lack fundamental incentives towards reducing agrochemical input. Instead, the primary motivation of most farmers when acquiring online information will be limited to increase yields and stabilize farming incomes. This is particularly the case for smallholders, who are by economics nature rather risk-reducers rather than input-optimizers. This might lead to a situation where information, even if it is obtained, understood, acknowledged, and translated in concrete measures, does not lead to a related behavioral change.

Despite rigorous analyses, we acknowledge a few limitations of our paper:

First, despite covering five province, the dataset can not be considered representative for all of China. Hence, research based on this dataset can only be suggestive when applied to other regions. Furthermore, our sample mainly includes family farms; other types of farms, such as agribusiness and large state farms, are not included in this sample. Second, we acknowledge limitations in measuring agrochemical quantities due to the substantial heterogeneity among available products, including differences in active ingredient concentrations and formulations. We could not assess the quantity of agrichemicals, in terms of active ingredients, based on the data we have. Considering the various brands and types of fertilizers and chemicals, it is challenging to identify and measure their active ingredients. More specialized data collections, for instance, collecting pesticide and fertilizer logs, if available, and product labels, could allow more precise dynamics with respect to agrochemical use. Third, although our findings suggest that differences in chemical fertilizer and pesticide use behaviour may indicate potential environmental impacts, it's difficult to assess the environmental efficiency of fertilizer and pesticide use solely through analysis of input costs and application frequencies. In particular, this cannot fully capture the environmental effects, since more environmentally friendly fertilisers may also be more expensive. Therefore, caution is advised when interpreting the results in this regard. Nevertheless, several studies have documented that smallholder farmers in China tend to apply inputs at levels exceeding recommended agronomic standards (Ju *et al*. 2009; Zhang *et al*. 2013), suggesting that input reduction policies may still be warranted. Future research is needed to measure direct environmental impact in more detail, depending on the type, quantity, and form of application. Panel data with several years of observations would help to fully control for endogeneity. Fourth, a deeer analysis of farmers' decision-making processes, particularly the motivations behind selecting specific amounts and types of chemical fertilizers and pesticides (e.g., increasing yields, preventing losses), was beyond the scope of this study. Future research could, for example, use interaction models or subgroup analyses to uncover mechanisms, e.g., whether usage is driven by price sensitivity, labor constraints, or technology exposure.

6. Conclusion and policy recommendations

The featured paper aimed at analyzing the fertilizer and pesticide input choices of Chinese family farmers and their interconnection with online agricultural information along a Propensity Score Matching approach. Our findings imply that, despite the potential of reducing fertilizier and pesticide input when following agronomic and political recommendations distributed in online sources, the use of these technologies actually was related to increased use of agrochemical inputs in our sample. As discussed above, this surprising finding can be explained by the superficial and biased use of online information, as well as barriers of generally low education and low digital literacy among our sample. These findings indicate that the ongoing digital revolution in China's agriculture should go hand in hand with capacity building measures as well as information campaigns increasing appropriate use of technology and information.

Based on the results of our study, some careful policy-relevant conclusions can be drawn that are likely valid for family farms across the country.

First, to tackle the mismatch between information demand and supply with respect to nature and specificity of information, local governments could support the provision of tailored information content and accessible platforms on sustainable farming practices and more precise expert advice on crop requirements under specific soil conditions. Considering the diverse farming structures across regions, local governments should innovate soil-testing methods, explore modern nutrient-diagnosis technologies, and leverage

the Internet to enhance information services. This approach would help farmers access regionally-tailored agricultural information online, ensuring they receive guidance appropriate to their specific circumstances.

Second, our findings suggest a need for targeted information interventions and trainings aimed at smallholders, tackling the mismatch between the presentation of information and reception ability of farmers. Such intervention would avoid that low-barrier marketing information remains the sole external information source for these farmers. Within our sample, only 10.1% of sampled farmers had received pesticide application training. Tailored training programs focused on reducing chemical fertilizer and pesticide use and improving efficiency could guide agrochemical application to be more effective, efficient, and eco-friendly. With a pressing need to raise awareness of sustainable development, more farmers could be encouraged to participate in sustainable farming activities. In general, improving farmers' digital literacy deserves greater attention. Over half of our sample farmers do not use online agricultural information in their production activities and rely exclusively on traditional channels. To date, few training initiatives aim to educate smallholders on how to interact with professional agricultural information online. Therefore, while enhancing rural digital infrastructure, the government should provide relevant ICT training to help farmers adapt to informatization and digitalization. For instance, South Korea has implemented successful programs to strengthen ICT skills among elderly farmers by offering tailored digital literacy training, helping them integrate digital tools into farming practices (Kang H *et al*. 2023).

Third, to increase the trust of farmers in offered innovation, local demonstration sites as analog complement to online information have shown to be an effective measure towards increasing the observability and trialability of adjusted input management in a no-risk environment. While there is a large number of initiatives active, more localized sites could help improving adoption also among smallholders with low mobility.

Finally, one main aim should be to increase incentive compatibility with respect to agrochemical use. While generally reducing subsidization for agrochemicals might harm especially smallholders and thus reduce the still important social security function of Chinese agriculture, other measures are conceivable. For instance, subsidization could be limited to environmentally friendly, "green" products or input exceed certain thresholds. Furthermore, a more strict implementation of existing dosage recommendations will be necessary. For instance Zhejiang government has launched an "Action Plan for Reducing the Quantity of Chemical Fertilizers/Pesticides", not only banned or is phasing out the sale of specific items but also monitoring the sales of products and even launching traceability initiatives for particularly critical substances. A nationwide implementation of these practices would be crucial in bringing about true, sustainable behavioral change with respect to sustainable use of agrochemicals.

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Declaration of competing interest

The authors declare that they have no conflict of interest.

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work, the authors used Grammarly in order to improve the language grammatically. This is used to check the correct use of articles and prepositions, and the sentences and meaning are expressions of the authors. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the content of the published article.

Data availability

Data will be made available upon request.

Appendices associated with this paper are available at https://doi.org/10.1016/j.jia.2026.04.019

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