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How crop insurance influences agrochemical input use: Evidence from cotton farmers in China

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Abstract

Crop insurance is critical in risk management in global agricultural production (e.g. by helping stabilise farmers' incomes in the long term and reducing risk-bearing costs). In this paper, using field survey data on cotton farmers in Xinjiang, China, we examine the influence of crop insurance on farmers' behaviours regarding agrochemical inputs and aim to investigate the synergy between crop insurance and reductions in fertiliser and pesticide usage. We find evidence that crop insurance significantly negatively affects farmers' use of fertilisers and pesticides, as well as significantly positively affects their adoption of green agricultural technologies (GAT) that can replace or complement traditional fertilisers and pesticides. Moreover, our results reveal that compared with small-scale farmers, crop insurance has a stronger effect on large-scale farmers' use of agrochemicals. Finally, when the insured amount is higher or the relative deductible is lower, farmers are more likely to reduce fertiliser and pesticide usage and adopt GAT. Overall, this paper scientifically identifies crop insurance can improve farmers' agrochemical input behaviour, by reducing farmers' use of traditional agrochemical inputs and increasing their adoption of GAT, which is of great significance for ensuring the safety of the agricultural ecological environment.

KEYWORDS

agrochemical use, cotton farmers, crop insurance, insurance terms, production scale

JEL CLASSIFICATION

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1 | INTRODUCTION

In recent decades, crop insurance has emerged as an effective method of reducing risks and losses and protecting agricultural production, and it has proven to be an essential element to improve agricultural risk management and competitiveness worldwide (Dougherty et al., 2020; King & Singh, 2020). Moreover, because crop insurance can replace direct government subsidy policies as a means of providing support and protection for agricultural development, it has become one of the most important nonprice agricultural protection measures (Fuchs & Wolff, 2011; Hill et al., 2019). Therefore, most governments support the rapid development of crop insurance through public financial means. For instance, in China, the country's crop insurance programme is continuing to grow in importance, with both the Chinese government and relevant departments successively issuing a range of guiding documents on the topic. For example, China's *No.1 Central Document* covering 2008 to 2020 provides clear guidance on crop insurance, and in the thirteenth Five-Year Plan, the Chinese government clearly proposes improving the crop insurance system. At present, subsidised crop insurance is the main instrument used in China to support farmers. Since China officially launched crop insurance subsidies in 2007, crop insurance has seen rapid development, with premiums increasing from 377 million yuan in 2004 to 67.25 billion yuan in 2019.[1]

Although crop insurance can stabilise farmers' incomes, it may prompt farmers to increase the amount of agrochemical inputs, which causes the deterioration of the ecological environment (Chang & Mishra, 2012; Lai, 2017). According to economic theory, moral hazard and adverse selection may affect farmers' production behaviour, such as management skills and the quality of input factors (Roll, 2019). Studies have shown that increasing agrochemical input use by farmers increases the expected output but also exacerbates fluctuations in output. Crop insurance can compensate for the lower-than-expected output, which can prompt farmers to increase their agrochemical input use (Zhong et al., 2007). Conversely, studies have also shown that both moral hazard and the adverse selection of crop insurance will reduce farmers' enthusiasm for factor inputs, causing them to reduce their agrochemical inputs. If the risk is an endogenous risk relating to the producer's behaviour and if the insurer cannot supervise the insured in the right way, moral hazard will occur (Wu et al., 2020). It can thus be seen that crop insurance changes farmers' agrochemical input behaviour by adjusting their expected income, and these changes can have positive or negative impacts on the ecological environment (Möhring et al., 2020; Urruty et al., 2016).

The effects of crop insurance on environmental policies not only depend on prevailing social and economic conditions but are also deeply affected by the heterogeneity of both insurance terms and farmers (Carter et al., 2016). On the one hand, due to large differences in agricultural production conditions (such as rainfall and climate), the crop insurance terms (such as protection level, premiums and starting point for claims) will vary depending on the area and crop. Different insurance terms have different risk-sharing capabilities and protection levels. Therefore, their impacts on farmers' agrochemical input behaviour will vary greatly. On the other hand, as a result of urbanised and nonagricultural development, the homogeneous pattern of farmers has been broken. Not only is the phenomenon of farmers' differentiation widespread, but also farmers of heterogeneous scales show obvious differences in agrochemical input behaviour (Hu et al., 2022). These developments mean that the impact and transmission mechanisms of crop insurance on the agrochemical input behaviour of previously heterogeneous farmers may have undergone important changes.

In general, existing research has concentrated on the effect of insurance participation on farmers' agrochemical input behaviour and has not considered the heterogeneity of insurance

[1]Data source: The China Insurance Yearbook.

terms, such as the impact of insurance amount and relative deductibles (or 'excess'), on such behaviour. Moreover, previous studies neglected the substitution relationships among agrochemical inputs and overlooked the function of crop insurance on farmers' agrochemical input and alternative technology adoption behaviour. In addition, studies on the impact of crop insurance on the input behaviour of agrochemicals by heterogeneous farmers are scarce (the detailed literature review can be seen in Appendix S3). There is large heterogeneity in farmers' production scales, which means that crop insurance policies can have more impact on the agrochemical input behaviour of some types of farmers compared with others. This paper evaluates the influence of insurance participation behaviour and insurance terms on farmers' agrochemical input behaviour and explores the substitution effect between agrochemicals.

The paper makes the following three contributions to the existing literature. First, this research elucidates how crop insurance influences farmers' agrochemical input behaviour from a new perspective, namely the heterogeneity of farmers' production scale. This builds on previous studies, which have only examined the causality between crop insurance and farmers' agrochemical input behaviour based on the assumption of farmer homogeneity, so our research perspective is unique. Second, based on a standard farmers' production decision-making model from the literature, this study not only examines the impact of farmers' participation in insurance on their agrochemical input behaviour but also analyses the impact of insurance terms (specifically the insurance rate and relative deductible rate) on their agrochemical input behaviour. Therefore, this paper expands the research scope of farmers' agrochemical inputs and technology adoption, and the research content has obvious novelty. Third, this research not only examines the influence of farmers' participation in insurance on their agrochemical input behaviour but also evaluates the impact of crop insurance on their technology adoption behaviour. Moreover, we explore the impact of crop insurance terms on farmers' agrochemical inputs and provide new research avenues for related research.

2 | CONCEPTUAL FRAMEWORK

Referring to the research of Feng et al. (2021), Hennessy (1998) and Quiggin et al. (1993), we construct a theoretical model to depict the impacts of crop insurance on farmers' agrochemical inputs against the background of China's crop insurance market. As ‘rational economic actors’, farmers can decide whether or not to invest in various production factors to maximise profits under certain risk conditions and market risks (Horowitz & Lichtenberg, 1993). The model assumes that a farmer's production goal is to obtain the maximum expected utility $\max EU$. Other model parameters are as follows: output per unit area is y; net income per unit area is π; output per unit area guaranteed by insurance companies is y^*; guaranteed price is p^*; cotton selling price is p; agrochemical input per unit area is x; other inputs are z; ω is an uncertain production environment (1 = risk-free state, and 2 = risky state); the random variable is ε; the agrochemical price is p_x; other cost per unit area is c; premium per unit area is $\rho(p^*)$; and area is M.

In the model, the production function $y = f(z, x, \omega, \varepsilon)$, where $a \le y \le b$ obeys probability density function $g(y)$. When the farmers do not participate in crop insurance, $p^* = 0$, $\rho(p^*) = 0$, where p^* measures the guarantee strength of insurance companies. Because farmers' premiums are proportional to the insurance company's guarantee strength, and because farmers' payment of premiums is rational, the insurance premiums that farmers need to pay are lower than what they expect as a payout from insurance companies under low-yield conditions. Therefore, $0 < \frac{d\rho}{dp^*} < \int_a^{y^*} (y^* - y)g(y)dy$. The expected utility function of farmers under the crop insurance framework is given by the following formula (1):

$$EU = \int_a^b U(\pi)g(y)dy, \text{where } U'(\pi) > 0, U''(\pi) < 0, \pi = \begin{cases} \pi_1, a \le y < y^* \\ \pi_2, y^* \le y \le b \end{cases} \tag{1}$$

$$\pi = 1M\left[py + p^*(y^* - y) - p_x x - c - \rho(p^*)\right] \tag{2}$$

$$\pi_2 = M\left[py - p_x x - c - \rho(p^*)\right] \tag{3}$$

When farmers do not participate in crop insurance, $p^* = 0$, and the premium per unit area $\rho(p^*) = 0$, where p^* measures the guarantee level of crop insurance. Depending on whether the output per unit area reaches the piecewise function of the insurance guarantee level, the profit function would be different. Here, π_1 and π_2 are two different profit functions.

In order to maximise the expected utility, the first-order condition is $\partial E\pi / \partial x = 0$. The first-order condition is 0, which is as follows:

$$\int_a^b U_\pi(\cdot)\pi_x(\cdot)g(y)dy = 0 \tag{4}$$

The derivative of x can be obtained as the optimal amount of the agrochemical input x. We take the first derivative of the expected utility to x and make it 0. It can be obtained using $x = x\left(p, p_x, p^*, c, \omega\right)$. Because this paper mainly focusses on the relationship between x and p^*, we find the total differential of the first-order condition as follows:

$$\begin{aligned}&\int_a^b \left(U_{\pi\pi}(\cdot)\pi_x(\cdot)\pi_x(\cdot) + U_\pi(\cdot)\pi_{xx}(\cdot)\right)g(y)dydx \\ &+\int_a^b \left(U_{\pi\pi}(\cdot)\pi_x(\cdot)\pi_{p^*}(\cdot) + U_\pi(\cdot)\pi_{xp^*}(\cdot)\right)g(y)dydp^* = 0\end{aligned} \tag{5}$$

$$w = \int_a^b \left(U_{\pi\pi}(\cdot)\pi_x(\cdot)\pi_x(\cdot) + U_\pi(\cdot)\pi_{xx}(\cdot)\right)g(y)dy, w < 0$$

Here, the second derivative of the utility in the first part is <0, and the square term is positive. The first derivative of the utility in the second part is >0, and the second derivative of the profit is equal to the second derivative of the output to x, which is negative. We can thus obtain:

$$\frac{dx}{dp^*} = -\frac{1}{w}\int_a^b \left(U_{\pi\pi}(\cdot)\pi_x(\cdot)\pi_{p^*}(\cdot) + U_\pi(\cdot)\pi_{xp^*}(\cdot)\right)g(y)dy \tag{6}$$

It can be obtained by calculation:

$$\begin{aligned}\int_a^b \pi_{p^*}(\cdot)g(y)dy &= M\left[\int_a^{y^*}\left[(y^* - y) - \frac{\partial\rho}{\partial p^*}\right]g(y)dy - \int_{y^*}^b \frac{\partial\rho}{\partial p^*}g(y)dy\right] \\ &= M\left[\int_a^{y^*}(y^* - y)g(y)dy - \frac{\partial\rho}{\partial p^*}\right] > 0\end{aligned} \tag{7}$$

$$\begin{aligned}\int_a^b \pi_{xp^*}(\cdot)g(y)dy &= M\left[\int_a^{y^*}\frac{(p - p^*)\frac{\partial y}{\partial x} - p_x}{\partial p^*}g(y)dy + \int_{y^*}^b \frac{p\frac{\partial y}{\partial x} - p_x}{\partial p^*}g(y)dy\right] \\ &= -M\int_a^{y^*}\frac{\partial y}{\partial x}g(y)dy = -M\frac{\partial\int_a^{y^*} yg(y)dy}{\partial x} < 0\end{aligned} \tag{8}$$

We cannot be sure whether $\pi_x(\cdot) = \frac{\partial \pi}{\partial x}$ is positive or negative. We can obtain:

$$\frac{dx}{dp^*} = -\frac{1}{w}\int_a^b \left(U_{\pi\pi}(\cdot)\pi_x(\cdot)\pi_{p^*}(\cdot) + U_\pi(\cdot)\pi_{xp^*}(\cdot)\right)g(y)dy \tag{9}$$

The core issue of concern is the influence of crop insurance on agrochemical inputs. This influence mainly depends on the impact of production factor inputs on a farmer's net income π under uncertain production. If a production factor input positively affects a farmer's income under different risk conditions, then $\frac{dx}{dp^*} < 0$. This result is also consistent with the existing literature (which found production factor investment reductions attributable to the moral hazard of purchasing insurance). However, the above assumptions are too strong for different types of production factors. Therefore, according to the different risk attributes embodied in different production factors, we divide production factors according to the existing literature. This differentiation was determined as follows:

First, if the production factor makes the marginal product smaller under risk-free disaster conditions than under disaster condition, that is, if $\frac{\partial f(z,x,1,\varepsilon)}{\partial x} \le \frac{\partial f(z,x,2,\varepsilon)}{\partial x}$, we define this factor as a risk-reducing factor. Second, if $\frac{\partial f(z,x,1,\varepsilon)}{\partial x} \ge \frac{\partial f(z,x,2,\varepsilon)}{\partial x} \ge 0$ is satisfied, this factor is defined as a weak risk-increasing factor. Lastly, if $\frac{\partial f(z,x,1,\varepsilon)}{\partial x} \ge \frac{\partial f(z,x,2,\varepsilon)}{\partial x}$ and $\frac{\partial f(z,x,2,\varepsilon)}{\partial x} < 0$ are satisfied, this factor is defined as a strong risk-increasing factor.

We further simplify the model. The expected profit function for farmers without insurance is as follows (where θ is the probability of a risk situation):

$$E\pi = (1-\theta)pf(z,x,1,\varepsilon) + \theta p(z,x,2,\varepsilon) - p_x x - c \tag{10}$$

The expected profit maximisation condition is $\frac{\partial E\pi}{\partial x} = 0$. Next, the expected profit function for farmers with insurance is as follows:

$$\begin{aligned} E\pi^* = {} & (1-\theta)pf(z,x,1,\varepsilon) + \theta pf(z,x,2,\varepsilon) \\ & + \theta p^*(y^* - f(z,x,2,\varepsilon)) - p_x x - c - \rho(p^*) \end{aligned} \tag{11}$$

According to the expected profit maximisation condition $\frac{\partial E\pi^*}{\partial x} = 0$, we can obtain:

$$\frac{\partial E\pi^*}{\partial x} - \frac{\partial E\pi}{\partial x} = -\theta p^* \frac{\partial f(z,x,2,\varepsilon)}{\partial x} \tag{12}$$

When a factor input is a strong risk-increasing factor, $\frac{\partial E\pi^*}{\partial x} > \frac{\partial E\pi}{\partial x}$. When the factor input is not a strong risk-increasing factor, $\frac{\partial E\pi^*}{\partial x} < \frac{\partial E\pi}{\partial x}$. Therefore, it can be seen that participating in crop insurance will affect farmers' expected incomes, thereby changing their production input behaviour. Compared with farmers without crop insurance, farmers with crop insurance have greater willingness to increase the use of strong risk-increasing factors and reduce the use of other types of production factors. In general, traditional agrochemicals (such as fertilisers and pesticides) reduce risk and increase yields. Green agricultural technology (GAT) (such as formula fertilisers and green pesticides) is different from traditional agrochemicals and can improve product quality and soil fertility (Tang & Luo, 2021). However, GAT is slow to take effect and its impact is weaker than that of traditional inputs. In addition, GAT is susceptible to external environmental factors. Therefore, GAT is considered to be a risk-increasing factor.

Based on these studies, we can argue that participation in crop insurance will promote farmers to adopt biological pesticides while reducing the adoption of chemical pesticides. First, compared with traditional production, GAT is a productive investment technology with long-term economic benefits and certain risks. Crop insurance can spread and transfer the risks of agricultural production and improve farmers' risk resistance, thus helping promote farmers' adoption of GAT (Gunnsteinsson, 2020; Karlan et al., 2014). Second, there is moral hazard when farmers participate in crop insurance. Such farmers reduce the use of traditional agrochemical inputs in order to receive insurance compensation after yield losses (Chambers, 1989). However, insurance terms stipulate that insurance companies are not responsible for yield losses caused by intentional acts of the insured. Consequently, to obtain compensation without violating the insurance terms, farmers participating in crop insurance choose to reduce the adoption of traditional agrochemicals and adopt GAT. Thus, the following hypothesis is proposed:

H1. Crop insurance will encourage farmers to reduce the use of agrochemical inputs while increasing their adoption of GAT.

Furthermore, the influence of crop insurance on farmers' agrochemical inputs is also related to production scale. Differences in endowments such as capital and land exist among farmers with different production scales. First, large-scale farmers have an advantage in terms of resource endowment compared with small-scale farmers. Crop insurance will therefore have a greater influence on their agrochemical input behaviour. Production scale is important in terms of access to crop insurance. Large-scale farmers with higher resource endowments are more capable of participating in crop insurance than small-scale farmers (Huang et al., 2020; Saqib et al., 2016). On the one hand, large-scale farmers have a stronger voice in fighting for compensation from insurance companies than small-scale farmers (Helfand & Taylor, 2020). On the other hand, in order to reduce transaction costs and supervision costs, insurance companies are more willing to sign contracts with large-scale farmers and have preferential policies for large-scale farmers (Santeramo et al., 2016). Insurance companies will also meet a greater part of the large-scale farmers' compensation requirements to increase their willingness to participate in insurance.

Second, large-scale farmers are more dependent on crop insurance than small-scale farmers. Therefore, crop insurance has a greater impact on their agrochemical input behaviour (Doherty et al., 2021; Enjolras & Sentis, 2011). Large-scale farmers face higher production risks. Their awareness of risk transfer and their tendency to participate in crop insurance are greater. Such participation, in turn, is conducive to boosting the adoption of GAT, thus reducing the use of traditional agrochemical inputs. Moreover, large-scale farmers are more focussed on long-term benefits and thus more inclined to adopt GAT, which can replace traditional agrochemicals (Bojnec & Latruffe, 2013; Helfand & Taylor, 2020).

Third, large-scale farmers have stronger financing capacity after participating in crop insurance than small-scale farmers. Thus, crop insurance has more influence on their agrochemical input behaviour. The 'credit + insurance' interaction model makes crop insurance an alternative and complementary element to pledges and guarantees. It can improve farmers' access to credit and ease their financing pressure (Giné & Yang, 2009), which helps farmers to adopt GAT. Additionally, production scale is important for the availability of agricultural credit. Large-scale farmers with larger production scales have greater credit availability after participation in insurance (Makate et al., 2019). Thus, it is proposed that:

H2. Compared with small-scale farmers, crop insurance has a greater influence on the agrochemical input behaviour of large-scale farmers.

At the same time, the premium rate, insurance amount and franchise deductible all depend on the average cost of inputs, production and subsidies. Therefore, the premium rate, insurance amount and deductible differ across different regions. That is, the guarantee level of crop insurance varies (Feng et al., 2021). Furthermore, the influence of crop insurance on farmers' agrochemical input behaviour also depends on the insurance terms. Specifically, crop insurance with higher coverage and a lower deductible shares more risk and provides farmers with higher degree of protection than insurance with lower coverage and higher deductible (Belissa et al., 2019). In turn, farmers tend to consider the coverage level when participating in crop insurance, which influences their production behaviour (Mol et al., 2020). The higher the coverage level of crop insurance, the more it helps to stabilise farmers' output expectations (Urruty et al., 2016; Yu et al., 2021). Therefore, farmers are more likely to reduce traditional agrochemical inputs and increase adoption of GAT (Möhring et al., 2020). Based on the above arguments:

H3. The higher the guarantee level of crop insurance, the greater the impact on farmers' agrochemical input behaviour.

Our hypotheses are summarised in Figure 1.

Based on the above theoretical analysis and in order to test the proposed hypotheses, this paper draws on the findings of previous empirical studies and selected farmers' agrochemical input behaviour as the dependent variable. The main independent variables are whether farmers participate in crop insurance and their production scale. We first establish a baseline model to explore the causality between crop insurance and farmers' agrochemical input behaviour. Then, we further use the Heckman two-stage regression model to explore the effect of insurance amounts and relative deductibles on farmers' agrochemical input behaviour. Additionally, we add the interaction term of crop insurance and production scale into the baseline model to discuss the different effects of crop insurance on farmers' agrochemical input behaviour due to different production scales. Accordingly, we build the following baseline model:

$$Y_i = \beta_0 + \beta_1 \times Insurance_i + \beta_2 \times Head_i + \beta_3 \times Household_i + \beta_4 \times Village_i + \varepsilon_1 \tag{13}$$

where Y_i is the dependent variable, representing farmers' agrochemical input behaviour, including the amount of fertiliser input, amounts of pesticide input and the adoption of GAT (soil testing, formula fertilisation and green pesticide technology). $Insurance_i$ refers to farmers' insurance participation behaviour. β_1 is the core coefficient of interest, which represents the effect of crop

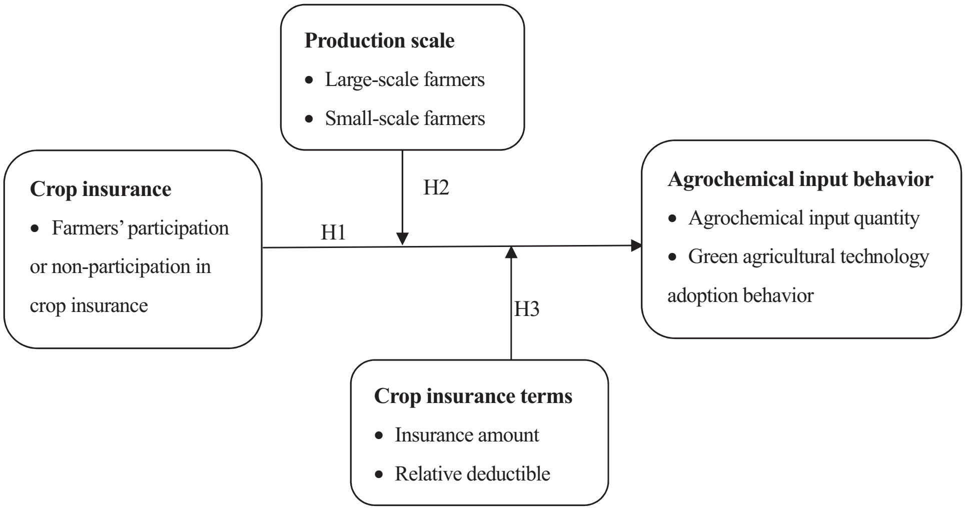

FIGURE 1 Analysis framework of crop insurances and agrochemical input behaviour.

insurance on farmers' agrochemical input behaviour. It can verify our Hypothesis 1. $Head_i$ is the characteristics of the head of household, such as age, gender, educational year and experience. $Household_i$ is the characteristics of households, such as family size, whether or not they are growers with the Xinjiang Production and Construction Corps (XPCC), hereafter referred to as Corps growers, whether their cotton fields are affected by a disaster of a certain degree, and the cotton field fertility over the years; ε_1 is a random perturbation term.

In addition, when analysing the influence of insurance terms on farmers' agrochemical input behaviour, we use the Heckman two-stage regression method to address the sample selection bias of farmers' participation in crop insurance. The first-stage regression equation is the equation of farmers' insurance participation behaviour, which is the factor influencing farmers' participation in crop insurance. The second-stage regression equation is the farmers' agrochemical input behaviour equation. That is, after correcting for the self-selection effect, the influence of insurance terms on farmers' agrochemical input behaviour is investigated. In summary, the Heckman two-stage regression model is set as follows:

$$Insurance_i = \gamma_0 + \gamma_2 \times Head_i + \gamma_3 \times Household_i + \gamma_4 \times Village_i + \varepsilon_2 \tag{14}$$

$$Y_i = \eta_0 + \eta_1 \times Term_i + \eta_2 \times Head_i + \eta_3 \times Household_i + \eta_4 \times Village_i + \varepsilon_3 \tag{15}$$

where Y_i is the dependent variable, representing farmers' agrochemical input behaviour. $Insurance_i$ refers to farmers' insurance participation behaviour. Other variables are the same as in model given in Eq. (13). This paper uses the maximum likelihood estimation method (MLE) to evaluate the Heckman sample selection model.

3 | DATA AND VARIABLES

3.1 | Data and sample

This study selects cotton farmers as the research object because the input amount of fertiliser per hectare (1 mu = 0.0667 hectare), the average amount of fertiliser converted into the pure amount per hectare and the pesticide cost for cotton are all higher than the average amounts for the three major grains of rice, wheat and corn. Specifically, referring to national agricultural product cost–benefit data collected over the 2005–2018 period (Price Department, National Development and Reform Commission of PRC, 2005–2018), the amount of fertiliser input per hectare of cotton increased from 1527.9 yuan/hectare in 2004 to 2921.4 yuan/hectare in 2017, the per-hectare pure fertiliser consumption increased from 382.5 kg/hectare in 2004 to 531.75 kg/hectare in 2017 and the cost of cotton pesticide increased from 487.35 yuan/hectare in 2004 to 1063.5 yuan/hectare in 2017 (1 yuan = 0.21 AUD = 0.15 USD in February, 2023).

Xinjiang was selected as the research area for several reasons. First, Xinjiang's cotton output has accounted for half of the domestic output of mainland China. In 2017, the cotton planting area was 2.2175 million ha, accounting for 69.41% of mainland China's total domestic area, and the output was 4565.984 million tonnes, accounting for 80.79% of mainland China's total domestic output, ranking first in China. Second, Xinjiang has prominent ecological and environmental problems and is facing severe ecological environment degradation, thereby creating urgent and realistic pressure for promoting green agricultural development. Third, Xinjiang's crop insurance premium income ranks first in China (the background of crop insurance in China is shown in Appendix S1). For example, in 2018, Xinjiang's crop insurance premium income was 4.851 billion yuan.

We conducted a presurvey in Xinjiang in August 2019, and launched the formal survey in October of the same year. The sample selection in the field survey adopts the multistage sampling method. We sampled in three stages: in the first stage, we selected Xinjiang local and XPCC as the sample areas based on comprehensive consideration of cotton planting area, corps and regional differences, and economic development. Specifically, according to the cotton planting area (the ratio of cotton planting area between local and XPCC is about 2:1), we selected two Xinjiang local regions (one each in southern and northern Xinjiang) and one division of the XPCC. In the second stage, we sorted the cotton yields for each county under the jurisdiction of each sample area in descending order, selected two sample counties in each area according to the principle of systematic sampling, selected two sample towns in each sampled county. A total of 12 sample towns were selected. In the third stage, we randomly selected two sample villages in each sample town. A total of 24 sample villages were selected.

Next, we numbered all farmers in each of the sample villages. Then, we randomly selected 15 farmers from each sample village, for a total of 360 sample farmers. In order to minimise data errors and ensure the accuracy and validity of the survey data, we invited experts to train the investigators before the formal survey was carried out. Furthermore, in order to overcome language barriers, we recruited bilingual students from Kashgar University as investigators for the survey in southern Xinjiang, where there are many ethnic minority farmers.

The content of the questionnaire covers farmers' individual characteristics, household characteristics, land use, agrochemical input behaviour, climate-adaptive technology adoption behaviour, risk preferences and other information. The data year is 2019. The survey was conducted through one-to-one interviews. A total of 360 questionnaires were completed. After excluding some questionnaires with missing information, 349 valid questionnaires were obtained, for an effective response rate of 96.94%.

3.2 | Variables

The dependent variable is farmers' agrochemical input behaviour, including amounts of agrochemicals used and GAT adoption behaviour. Among them, the amounts of fertiliser and pesticide were expressed as the amount of fertiliser used per mu and the amount of pesticide applied to treat cotton aphids per mu. Green agricultural technology was measured by soil testing formula fertilisation technology and green pesticide technology, which could replace traditional agrochemicals (Chèze et al., 2020).

The main independent variable is crop insurance participation, which is a dummy variable: a value of 1 indicates farmers participated in crop insurance; otherwise, its value is 0. Furthermore, farmers' agrochemical input behaviour may have a heterogeneous impact due to different insurance terms. High insurance coverage and low deductibles will protect farmers' production risks to a high degree (Belissa et al., 2019), which may promote farmers to increase investment. But it is also possible that due to moral hazards, farmers may reduce their agrochemical inputs. Therefore, to explore the influence of different insurance terms on farmers' agrochemical input behaviour, refinements of crop insurance terms, such as insurance amount and relative deductible, were selected.

In addition, we use actual arable areas, including both owned and leased arable land, to measure farmers' production scale (Helfand & Taylor, 2020). Also, we have controlled for age, gender, education, experience, family size, construction corps, cotton disasters and cotton field fertility. The older the head of a household is, the more likely they are to be accustomed to traditional planting concepts, and they probably do not adopt GAT (Jensen et al., 2014). Male-headed households and households with higher years of education and rich planting experience are more likely to use fertilisers and pesticides rationally. They are more accepting of new technology and pay more importance to green production (Vignola et al., 2010). Therefore, it is more likely for them to reduce the amount of fertilisers and pesticides and adopt

GAT. Furthermore, family size, cotton disaster, different production scale and different cotton field fertility levels can also affect farmers' agrochemical input behaviour (Khan et al., 2020).

Table 1 provides the variables' definitions and summary statistics. Among the 349 sample farmers, the insured rate of cotton farmers was 69.6%, and the average production scale was 447.7 mu. The average amount of fertiliser applied to the cotton fields in 2019 was 35.360 kg/mu (converted to a pure amount), and the pesticide application amount for cotton aphid treatment in 2019 was 0.099 kg/mu. The adoption rate of formula fertiliser technology instead of traditional fertiliser was 61.9%, and that of green pesticide technology was 60.7%. Additionally, we compared farmers' characteristics based on the cotton insurance

TABLE 1 Summary statistics.

Variables	Definitions	Mean	SD	Min	Max
Dependent variables					
Fertiliser input	The amount of fertiliser in cotton field in 2019 (kg/mu (converted to pure amount)).	35.360	13.910	9	81
Pesticide input	The amount of pesticide rate for cotton aphids in cotton field in 2019 (kg/mu).	0.099	0.034	0.015	0.170
Formula fertiliser	A dummy variable coded 1 if the cotton field adopts formula fertiliser technology in 2019, and zero otherwise.	0.619	0.486	0	1
Green pesticide technology	A dummy variable coded 1 if green pesticides are used to cotton fields in 2019, and zero otherwise.	0.607	0.489	0	1
Independent variables					
Crop insurance	A dummy variable coded 1 if the farmer buys crop insurance, and zero otherwise.	0.696	0.461	0	1
Production scale	Actual cotton planting area of farmers (100 mu)	4.477	14.480	0.032	160
Insurance amount	Actual value of insured amount (thousand yuan/mu)	0.567	0.396	0	1.600
Relative deductible	Relative deductible (%)	21.340	6.673	10	30
Control variables					
Age	Age of head of household (years old)	50.04	9.631	24	90
Gender	A dummy variable coded 1 if the head of household is male, and zero otherwise.	0.894	0.308	0	1
Education	Number of years that head of household has received education (years)	7.977	2.794	0	16
Experience	Experience of cotton cultivation (years)	15.33	9.617	0	50
Family size	Total number of households (person)	4.527	1.629	1	16
Construction corps	Yes = 1; No = 0	0.249	0.433	0	1
Cotton disaster	0—none; 1—weak; 2—moderate; 3—serious	1.158	0.980	0	3
Cotton field fertility	An indicator variable equal 1 if cotton field fertility is poor; 2—medium; 3—good; 4—excellent	2.309	0.759	1	4
Instrument variables					
Proportion of village insured	Actual insured proportion in the village	73.06	27.860	0	100
Government subsidy ratio	Government subsidy ratio of insurance cotton.	46.42	32.470	0	90

situation. We also performed t-tests on the two groups (results are given in Appendix S2: Table S1).

4 | EMPIRICAL ANALYSIS AND RESULTS

4.1 | Crop insurance and farmers' agrochemical input behaviour

First, we examine the impact of farmers' participation in crop insurance on their agrochemical input behaviour, which is reported in Table 2. Column (1) reveals the impact of crop insurance participation on farmers' fertiliser input behaviour. The results show that the sign on the crop insurance coefficient is negative and significant at the 1% level, which indicates that compared with noninsured farmers, farmers participating in crop insurance use lower amounts of fertiliser. Column (3) presents the effect of insurance participation on farmers' pesticide input behaviour. The result shows that the coefficient on crop insurance

TABLE 2 Crop insurance and farmers' agrochemical input behaviour.

	(1)	(2)	(3)	(4)
	Fertiliser input	Formula fertiliser technology	Pesticide input	Green pesticide technology
Crop insurance	−6.074***	0.117*	−0.025***	0.298***
	(1.844)	(0.064)	(0.004)	(0.059)
Production scale	−0.061**	0.003***	−0.001***	0.004***
	(0.031)	(0.001)	(0.000)	(0.001)
Age	0.096	−0.005	0.000	−0.005*
	(0.082)	(0.003)	(0.000)	(0.003)
Gender	−0.020	0.026	−0.007	0.071
	(2.465)	(0.084)	(0.005)	(0.076)
Education	0.009	0.006	0.001	0.000
	(0.282)	(0.010)	(0.001)	(0.009)
Experience	0.020	0.002	0.001***	−0.007**
	(0.085)	(0.003)	(0.000)	(0.003)
Family size	0.555	−0.006	0.000	−0.009
	(0.429)	(0.016)	(0.001)	(0.015)
Construction corps	−4.168**	0.173***	0.000	0.012
	(1.649)	(0.066)	(0.004)	(0.065)
Cotton disaster	−1.671**	0.055**	−0.000	0.078***
	(0.707)	(0.027)	(0.002)	(0.024)
Cotton field fertility	−2.549***	0.059*	0.002	−0.025
	(0.975)	(0.032)	(0.002)	(0.034)
Constant	41.049***	0.388	0.083***	0.614***
	(6.386)	(0.239)	(0.015)	(0.229)
Observations	349	349	349	349
R^2	0.164	0.115	0.228	0.219

Note: ***, ** and * are significant at the level of 1%, 5% and 10%, respectively; Robust standard errors are in brackets.

is significantly negative at the 1% level, which clearly demonstrates that compared with noninsured farmers, farmers participating in crop insurance apply lower amounts of pesticide, after controlling for other influencing factors. This finding indicates that crop insurance can directly affect farmers' agrochemical input behaviour through moral hazard. In addition, insurance can indirectly affect their agrochemical input behaviour by encouraging farmers to adopt agrochemical substitution technology.

On one hand, crop insurance can spread agricultural production risks and compensate for agricultural production losses. The moral hazard and adverse selection effects under the crop insurance system will restrain farmers' willingness to invest in upgrading their agricultural technology because such upgrades are not needed to hedge against crop losses given that insurance will compensate them instead. Accordingly, crop insurance can lead to complacent or negligent farm management behaviour, leading to farmers reducing their inputs of agrochemicals. On the other hand, excessive application of pesticides and fertilisers is related not only to farmers' planting structure but also to their risk-aversion psychology (Liu, 2013). Crop insurance can reduce the production risks faced by farmers, but the guarantee level offered by crop insurance at this stage is relatively limited. Farmers will therefore not significantly reduce their use of agrochemicals a priori, but may adopt GAT that can replace agrochemicals, thereby leading to reductions in agrochemical use following the adoption of such alternative technologies.

Moreover, Xinjiang cotton insurance only covers some costs that materialised in the cotton production process in the year of a disaster. The expected claim amount of cotton farmers in Xinjiang is far less than that of European and American farmers' yield insurance. In fact, the claim threshold is less than two times the standard deviation of the average yield. In a year with no harvest, the maximum claim could only be 60% of the average material cost. Under the current insurance terms, farmers have less incentive to pursue insurance claims by increasing the input of fertilisers and pesticides to increase expected yields, resulting in greater yield fluctuations (Zhong et al., 2007).

Next, the influence of crop insurance on the adoption of GAT by farmers is tested. The results are shown in Table 2. Column (2) shows the influence of crop insurance on farmers' formula fertiliser technology adoption behaviour. Column (4) presents the effect of crop insurance on farmers' green pesticide technology adoption behaviour. These results show that compared with noninsured farmers, farmers participating in crop insurance are more likely to adopt soil testing formula fertilisation technology and green pesticide technology. The reason for this finding could be as follows. Uncontrollable production risks and information asymmetry mean that when farmers make decisions regarding agricultural production, they must consider not only profit maximisation but also risk minimisation (Cole et al., 2013; Liu, 2013). Farmers have very limited tolerance for unplanned risks such as natural disasters in agricultural production, and they adopt conservative production behaviours in order to reduce risks in production decisions. However, as a policy to spread agricultural production risks, stabilise farmer incomes, compensate for economic losses and promote agricultural development, crop insurance can significantly reduce conversion/switching risks and any higher risks arising after switching to agrochemical substitution technologies, thereby guaranteeing farmers' incomes (Tang & Luo, 2021; Visser et al., 2019).

We also use seemingly unrelated regressions (SUR) to systematically estimate the regression equations of farmers' fertiliser input, formula fertiliser technology, pesticide input and green pesticide use as a robustness check of the baseline results. The results show that the p-value of 'no synchronous correlation' between the disturbance terms of the equations is 0.000, so the null hypothesis that the equations' disturbance terms are independent can be rejected at the 1% level. The results of the SUR do not different much from the OLS results (see Appendix S2: Table S2). Moreover, we used the multinomial logit model to analyse farmers' agrochemical input behaviour, and the results show that crop insurance can reduce agrochemical inputs and promote farmers' adoption of GAT, indicating our baseline results are robust (see Appendix S2: Table S3).

In addition, the results show that farmer's production scale and agrochemical input use each have a significantly negative coefficient, whereas the coefficient on agrochemical substitution technology adoption is significantly positive. These findings show that, after controlling for other influencing factors, as the scale of cotton planting increases, the input levels of fertiliser and pesticide become more moderate.

4.2 | Addressing endogeneity

Determining causality between crop insurance and agrochemical input behaviour is the core issue of this study. We cannot observe the effects of the same farmer's behaviour regarding agrochemical input behaviour both with and without possessing crop insurance at the same time. Therefore, we are also unable to directly assess the impact of crop insurance on farmers' agrochemical input behaviour. There is endogeneity between crop insurance and farmers' agrochemical input behaviour. In terms of explaining such endogeneity, first, reverse causality could be present. There may be mutual influences between agrochemical inputs, and a causal relationship has been demonstrated to exist between crop insurance and farmers' agrochemical input behaviour, which will lead to endogeneity problems. On the one hand, crop insurance has the function of avoiding risks, which can protect farmers' incomes, thereby affecting their agrochemical input behaviour. On the other hand, farmers with more reasonable (i.e. rational) investments in agrochemicals are more able to participate in crop insurance. For their own benefit, insurance companies reduce the insurance claim rate and prefer to sign contracts with farmers having better production conditions. Therefore, there may be mutual causality between crop insurance and farmers' agrochemical input behaviour.

The second issue could be missing variables. Farmers' agrochemical input behaviour is affected by many economic and cultural factors (Chang & Mishra, 2012). Due to the limitation of data availability, it is difficult to control for all such factors. If important variables (such as farmers' IQ, personal capabilities and environmental awareness) related to crop insurance participation are omitted from the model, it will cause endogeneity problems. Third, self-selection problem could be present. Farmers' participation in crop insurance is not randomly assigned but can be seen as their optimal choice under various constraints. The decision-making regarding crop insurance participation thus has the characteristics of self-selection (Zhong et al., 2007). To some extent, farmers' agrochemical input behaviour and insurance participation behaviour offer the possibility of 'simultaneous decision-making', resulting 'self-selection' in view of their individual characteristics and comparative advantages. If these possibilities are ignored, the estimated result of crop insurance's impact on farmers' agrochemical input behaviour is biased.

Crop insurance is considered an endogenous variable. To deal with the endogeneity of crop insurance, we first use the instrumental variable (IV) method to overcome any potential endogeneity. Following the method of Feng et al. (2021), Hill et al. (2019) and Zhong et al. (2007), we adopt the insured percentage in a village (average intensity of crop insurance promotion in a village) and insurance subsidies ratio (policy support intensity) as the IV of farmers' insurance participation behaviour. The result of the Hausman test [8.88 (p-value 0.012)] indicates that the hypothesis that 'all independent variables are exogenous' is rejected.

An IV's rationality depends on its relevance conditions and exclusivity constraints. The relevance condition requires that the IV is related to the endogenous variable (crop insurance) and has nothing to do with the unobservable factors that affect the farmers' agrochemical input behaviour. On one hand, governments usually take action to urge farmers to participate in crop insurance, most commonly by providing substantial subsidies (Santeramo et al., 2016). On the other hand, villages play an important role in farmers' decisions to participate in crop insurance, especially at the beginning of crop insurance programmes. In the same village, it is common for families' decision-making to show a certain correlation. For example, farmers can refer to the participation of other villagers to make decisions (Li et al., 2022; Tang & Luo, 2021; Wang et al., 2016).

Second, for the exclusivity constraints, we believe that in the case examined in this study, the insured percentage in a village and insurance subsidiaries ratio are unlikely to directly affect the farmers' agrochemical input behaviour. This is because the insurance participation rate and insurance subsidies in a region usually refer to the average intensity and policy support intensity of crop insurance promotion in the village, which is unlikely to directly affect farmers' production behaviour (Feng et al., 2021). Some regions were observed to provide an insurance subsidy (i.e. similar to discount coupons) to all farmers, meaning that only those who participate in the insurance can benefit from cost-sharing. Thus, from a theoretical point of view, the insured percentage in a village and the insurance subsidies ratio will directly affect farmers' insurance participation behaviour, but will not directly affect farmers' agrochemical input and GAT adoption behaviour, thereby satisfying correlation and exogenous assumptions.

Table 3 presents the results of the two-stage least-squares method (2SLS). It can be seen that the two IVs and endogenous variables are both significant at the 1% level. Additionally, the Kleibergen–Paap rk LM statistic shows that the IV satisfies the correlation condition, and the F-statistics in the first stage are 1308.639, which is greater than the critical value of the Cragg–Donald statistics (Stock & Yogo, 2005). It indicates that there is not a problem with weak IVs. Also, the p-value of the overidentification fails to pass the significance test at the 10% level [1.76 ($p = 0.185$)]. Thus, our IV passes the overidentification test. The resulting coefficient for the IV changes slightly, but the previous conclusions are not changed, showing that the results are robust.

The results of the first stage show that a farmer's production scale, the insured percentage in the village and the insurance subsidy ratio significantly influence farmers' participation in insurance. Normally, large-scale farmers are more willing to participate in insurance compared with small-scale farmers because they suffer more severe losses from natural disasters, and compared with small-scale farmers, it is easier for large-scale farmers to obtain formal crop insurance to reduce risks. Moreover, government subsidies have a significant role in promoting farmers' participation in insurance. Generally speaking, government subsidies can reduce the cost of sharing farmers' participation in insurance and can thus significantly promote participation. Additionally, referring to Lewbel (2012) and using the heteroscedastic identification strategy, we attempt to construct IVs for crop insurance (the results and details are given in Appendix S1: Table S4).

5 | ADDITIONAL ANALYSIS

5.1 | Crop insurance and agrochemical input behaviour of heterogeneous-scale farmers

The aforementioned empirical research indicates that crop insurance significantly affects farmers' agrochemical input behaviour. Now, we extend our approach to analyse the different impacts of crop insurance on the farmers' agrochemical input behaviour among farmers with heterogeneous production scales. The econometric model is as follows:

$$Y = \alpha_1 + \alpha_2 \times Insurance_i + \alpha_3 \times Scale_i + \alpha_4 \times Insurance_i \times Scale_i + \alpha_5 \times X + \varepsilon_4 \quad (16)$$

TABLE 3 Addressing endogeneity: Instrumental variable estimation.

	First stage	Second stage			
	Insured or noninsured	Fertiliser input	Formula fertiliser technology	Pesticide input	Green pesticide technology
	(1)	(2)	(3)	(4)	(5)
Crop insurance	——	−5.974***	0.109	−0.024***	0.316***
	——	(1.948)	(0.070)	(0.004)	(0.065)
Proportion of village insured	0.002***	——	——	——	——
	(0.001)	——	——	——	——
Insurance subsidy ratio	0.012***	——	——	——	——
	(0.000)	——	——	——	——
Control variable	Yes	Yes	Yes	Yes	Yes
Constant	−0.183**	40.055***	0.403*	0.082***	0.640***
	(0.072)	(6.281)	(0.236)	(0.015)	(0.225)
First-stage F-statistic	1308.639***				
Cragg–Donald minimum eigen value	19.93				
Sargan statistic	1.760				
	(0.185)				
Observations	349	349	349	349	349
R^2	0.917	0.177	0.117	0.232	0.230

Note: ***, ** and * are significant at the level of 1%, 5% and 10%, respectively; Robust standard errors are in brackets. In the model, variables such as farmer characteristics, family characteristics and planting characteristics were controlled.

where $Scale_i$ is the farmers' production scale, measured by their actual cotton planting area. $Insurance_i \times Scale_i$ is the interaction term between the farmers' insurance participation behaviour and their production scale, which is used to measure the difference in the influence of insurance participation on agrochemical input behaviour among farmers with heterogeneous production scales. The definitions of other variables are consistent with those given in relation to Eq (13). Here, α_4 is the key coefficient of interest, and it indicates the moderating effect of the production scale on crop insurance's influence on farmers' agrochemical input behaviour.

The results indicate that as production scale expands, crop insurance has an increased inhibitory effect on farmers' agrochemical input use while promoting greater adoption of agrochemical substitution technology. In 2019, the survey of cotton farmers carried out for this study found that large-scale and small-scale farmers pay different insurance fees. In addition, subsidy policies vary greatly among farmers in different regions and sizes. At different production scales, the cost of insurance is different, and the proportion of the premium subsidy is lower for large-scale farmers. Large-scale farmers have higher resource endowments and face greater risks than small-scale farmers (Saqib et al., 2016). The influence of crop insurance on the farmers' agrochemical input behaviour can vary depending on their production scale.

Furthermore, the probability of receiving compensation is closely related to production scale. Large-scale farmers have a stronger voice in the amount of compensation compared with small-scale farmers because their larger production scale confers them with greater bargaining power. Large-scale farmers also have more concentrated land, allowing for compensation based on the actual yield loss of the plot. For small-scale farmers, the production scale is small, and individual fields are dispersed and often widely separated, thereby reducing their collective power and ability to unify to place more pressure on insurance companies for better payouts.

When negotiating with insurance companies, farmers' leverage to ask for higher compensation cannot outweigh the insurance company's ultimate ability to decide on the payout amount. Because insurance companies cannot pay according to the specific land area and actual loss rate, the probability of obtaining sufficient compensation is low. Therefore, compared with small-scale farmers, crop insurance more strongly affects large-scale farmers' agrochemical input behaviour and GAT adoption (Table 4).

To verify the robustness of the conclusions, we use the subsamples of 'insured' and 'non-insured' farmers for further analyses; these subsamples are also used to check the robustness of the interaction term model. In addition, to investigate the different influences of crop insurance on the agrochemical inputs of farmers with different production scales, this paper carries out group regression according to the median of farmers' production scale, larger than the median is the large-scale farmers, otherwise it is the small-scale farmers, which is used as the robustness test of cross-term regression. The results indicate that crop insurance has a greater effect on large-scale farmers' agrochemical input and GAT adoption (results are given in Appendix S2: Tables S5 and S6).

5.2 | Insurance terms and farmers' agrochemical input behaviour

The influence of crop insurance on farmers' agrochemical input behaviour depends not only on the agricultural production environment but also on the nature of crop insurance terms and degree of risk-sharing. For example, suppose that insurance contract A and insurance contract B have the same insured amount (900 yuan/mu), but the deductible rate of contract A is 10%, whereas the deductible rate of contract B is 20%. Obviously, the risk protection level of contract A is greater than that of contract B. However, if measured only in terms of whether to participate in crop insurance given the insured amount, contract A and contract B appear to have the same protection level, which is not in line with reality. Therefore, we further consider the heterogeneity of insurance terms and analyses the impact of specific insurance terms on farmers' agrochemical

TABLE 4 Crop insurance and agrochemical inputs: Heterogeneous-scale farmers.

	(1)	(2)	(3)	(4)
	Fertiliser input	**Formula fertiliser technology**	**Pesticide input**	**Green pesticide technology**
Crop insurance	−6.395***	0.112*	−0.025***	0.313***
	(1.840)	(0.067)	(0.004)	(0.062)
Production scale	0.003	0.002	−0.000*	0.002**
	(0.044)	(0.001)	(0.000)	(0.001)
Crop insurance × Production scale	−4.879**	0.134*	−0.009*	0.121*
	(2.278)	(0.075)	(0.005)	(0.072)
Control variable	Yes	Yes	Yes	Yes
Constant	40.561***	0.392	0.083***	0.631***
	(6.384)	(0.240)	(0.016)	(0.231)
Observations	349	349	349	349
R^2	0.189	0.124	0.239	0.235

Note: ***, ** and * are significant at the level of 1%, 5% and 10%, respectively; Robust standard errors are in brackets. In the model, variables such as farmer characteristics, family characteristics and planting characteristics were controlled.

input usage and agrochemical substitution technology adoption. The results are presented in Table 5. The higher the insured amount and the lower the crop insurance deductible, the lower the amount of agrochemicals used by farmers and the higher their probability of adopting GAT.

Considering that we only use the sample of farmers participating in crop insurance to evaluate the influence of insurance terms on the farmers' agrochemical input behaviour, all sample information on the agrochemical input behaviour of uninsured farmers will be discarded, and the sample of insured farmers may not be a randomly selected subsample. This will lead to problems such as sample selection bias, and the sample cannot represent the overall population well. Therefore, we use the Heckman two-stage regression model to further solve the selection

TABLE 5 Crop insurance terms and farmers' agrochemical input behaviour.

	(1)	(2)	(3)	(4)
	Fertiliser input	**Formula fertiliser technology**	**Pesticide input**	**Green pesticide technology**
Insurance amount	−4.944*	0.395***	−0.027***	0.087
	(2.683)	(0.070)	(0.006)	(0.096)
Relative deductible	0.351**	−0.022***	0.000	−0.009
	(0.175)	(0.004)	(0.000)	(0.006)
Production scale	−0.055*	0.003***	−0.000***	0.004***
	(0.030)	(0.001)	(0.000)	(0.001)
Control variable	Yes	Yes	Yes	Yes
Constant	30.309***	0.918***	0.070***	0.837***
	(8.064)	(0.221)	(0.019)	(0.287)
Observations	349	349	349	349
R^2	0.190	0.382	0.243	0.126

Note: ***, ** and * are significant at the level of 1%, 5% and 10%, respectively; Robust standard errors are in brackets. In the model, variables such as farmer characteristics, family characteristics and planting characteristics were controlled.

TABLE 6 Crop insurance terms and farmers' agrochemical input behaviour: Heckman model.

	(1)	(2)	(3)	(4)
	Fertiliser input	**Formula fertiliser technology**	**Pesticide input**	**Green pesticide technology**
Insurance amount	−10.465**	1.430**	−0.025**	0.259
	(4.417)	(0.615)	(0.011)	(0.632)
Relative deductible	0.447**	−0.086***	0.000	−0.047*
	(0.206)	(0.028)	(0.000)	(0.026)
Production scale	−0.053*	0.014**	−0.000***	0.016**
	(0.028)	(0.006)	(0.000)	(0.006)
Control variable	Yes	Yes	Yes	Yes
Constant	−6.108***	−5.902***	−6.012***	−5.911***
	(1.054)	(1.021)	(1.031)	(1.019)
Observations	349	349	349	349
Selected	243	243	243	243
Wald value	37.45***	34.76***	35.08***	29.40***

Note: ***, ** and * are significant at the level of 1%, 5% and 10%, respectively; Robust standard errors are in brackets. In the model, variables such as farmer characteristics, family characteristics and planting characteristics were controlled.

bias so that the results are more scientifically explanatory. The first stage is to explore whether farmers are insured, and the second stage analyses the influence of insurance terms on farmers' agrochemical input behaviour. The results of Heckman two-stage estimation are shown in Table 6. The coefficients of the results have changed slightly, but the basic conclusions of the previous analyses remain unchanged.

6 | CONCLUSIONS AND IMPLICATIONS

This study aimed at examining the causality between crop insurance and farmers' agrochemical inputs and GAT adoption behaviour in China. Moreover, we also assess the moderating effect of production scale on crop insurance's effect on agrochemical input use behaviour. First, after controlling for variables affecting farmers' agrochemical input behaviour as identified by prior studies, crop insurance is found to have a significant effect on average amount of fertiliser and pesticide by reducing the average input of fertiliser and pesticide per mu. Second, crop insurance contributes significantly to promoting GAT, which can replace traditional fertilisers and pesticides. Third, compared with the impact on small-scale farmers, crop insurance more strongly affects the per-mu fertiliser amount, pesticide application and GAT adoption behaviour for large-scale farmers. Fourth, the higher the insurance percentage and insurance amount, and the lower the relative deductible, the more likely farmers are to reduce fertiliser and pesticide usage and adopt GAT. This states clearly that encouraging farmers to participate in crop insurance with low-premium and low-indemnity terms will not have a significant negative influence on the environment.

Our findings provide some insight into the experience of one developing country's use of crop insurance. Crop insurance can guarantee agricultural production and stabilise farmer incomes. It is an important means to avoid agricultural risks and make up for farmers' economic losses. It is also an active policy tool instrument for improving the risk control system during the agricultural transformation and upgrading period of developing countries (Hill et al., 2019). At the same time, many developing countries are also experiencing rapidly increasing intensity of agrochemical use, which will affect the long-term sustainable development of agriculture (Feng et al., 2021). These countries are also facing similar challenges in reducing agrochemical use. Therefore, the promotion of crop insurance should focus on its possible effect on farmers' agrochemical input behaviour. This study shows that under the current insurance terms, crop insurance will not lead to deterioration of the ecological environment. Moreover, the crops in Xinjiang, especially the cotton crops we studied here, are single-season crops. Promoting crop insurance will therefore not increase deterioration of the ecological environment. Therefore, the government should keep on supporting and promoting crop insurance.

The findings in this study have the following policy implications. First, this paper confirms that crop insurance can reduce farmers' agrochemical input use and promote the adoption of GAT. It further illustrates that against a background of widespread overapplication of fertilisers and pesticides, crop insurance can induce farmers to reduce agrochemical input usage. Government departments should emphasise the role of crop insurance in the green development of agriculture, thereby improving the rural ecological environment and guaranteeing farmer incomes.

Second, in the case of the current insurance terms used for cotton in the study area, increases in the insurance amount and decreases in the relative deductible ratio encouraged farmers to reduce the amount of agrochemical inputs they use. Therefore, it is important to encourage the integrated development of multiple types of insurance with different insurance amounts and different relative deductibles in order to reduce the environmental degradation caused by the crop insurance system. Third, the results of this study strongly indicate that large-scale farmers are more willing to reduce their agrochemical input use and adopt GAT. Promoting the scale production of farmers can reduce agrochemical input levels, which is an effective measure in promoting the green development of agriculture. Therefore, when encouraging farmers to reduce agrochemical inputs and adopt GAT, it is necessary to formulate corresponding policies according to the scale of farming production. Accordingly, the government should encourage the transfer of land to new agricultural business entities such as large professional growers, make more complete institutional arrangements for nonagricultural employment and rural social security, promote the development of large-scale farmers, eliminate environmental degradation under the crop insurance system and ensure the sustainable development of China's agriculture.

This paper has the following limitations. First, we use cross-sectional data. However, in exploring the impact of crop insurance on agrochemical use, continuous multiperiod panel data are better. Therefore, in further analyses, we will consider the use of panel data to investigate the dynamic impact of crop insurance on agrochemical use. Second, this paper only considers crop insurance related to cotton. We will increase the survey to include other crops in future in order to expand the universality of the research findings. Third, we only interviewed 360 cotton farmers. When we explore the influence of crop insurance on farmers' agrochemical input behaviour, more samples would be needed to ensure the significance of the results. In subsequent follow-up research, we will expand the sample size to increase the reliability of the results.

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DATA AVAILABILITY STATEMENT

Availability of data and material: The datasets generated are available from the corresponding author on reasonable request. Code availability: The code generated during the current study are available from the corresponding author on reasonable request.

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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